GENETIC ALGORITHMS IN E-LEARNING SYSTEMS

Sargsyan S. G., Hovakimyan A.S., Barkhudaryan S.V.

Abstract: - *An approach for the problem of building such tools of e-learning system that gives the user a chance to get the desired knowledge of teaching course in a user adaptable manner is suggested in this article. This approach is based on so-called "teaching scenarios" (sequence of teaching units) being constructed during the process of learning. We introduce a tool that builds user adaptable teaching scenarios based on Genetic Algorithms, built-in the Genetic Chooser Algorithm (GCA). These scenarios are being constructed via the quality and quantity characteristics of the teaching units and user's knowledge. A course-map building tool is also introduced in GCA that helps user to see his /her progress through the course. The considered method is realized and introduced in the TeachArm e-learning system [S.G. Sargsyan, A.S. Hovakimyan, and all, 2002]*

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Introduction

We have a teaching course and are going to construct such a system that would organize the whole material in such a way that will make the process of learning easy and effective for the user.

The teaching process in learning systems is presented as separate teaching cycles, and each ends with testing the user's knowledge. Several types of teaching scenarios are distinguished: free, fixed and manageable via the teaching system. The third one is generated by the teaching system during the teaching process. The teaching material is divided into logical units that a teaching scenario is constructed of. Having the users' base of knowledge after a test, user is offered a scenario to study. A scenario is being constructed of teaching units sequenced in a way that provides a learner an effective way to get new knowledge.

An approach is suggested to solve this problem. It is worth mentioning that a solution will be an acceptable one rather than an exact one because Genetic Algorithm is an approximation method. In particular an exact solution for this kind of problems is almost impossible to find because they have a very large set of possible solutions where we will have to search the exact solution from. Besides no two learners are the same. They are of different backgrounds and different knowledge-base, which makes difficult to define exactly what does a good solution mean for a particular learner.

We find a user adaptable scenario of a teaching process phase using GA [Z. Michalewicz, 1999], [George F. Ludger, 2003]. A course-map building tool, which also shows a user's progress through the course, is implemented using L-Systems [Jon McCormack, 2003].

The Problem and the solution model

The problem is the following. Organize an effective teaching system having the teaching material and information about learner's knowledge base. We will define such concepts as teaching scenario, dependency matrix, teaching stage for a learner, acceptable scenario. Saying effective teaching we understand giving the next best teaching scenario to the learner in the given teaching stage taking into account the level of knowledge that the learner has gained studying the past teaching scenario.

Let's define the mathematical model for this problem.

Let's mark the teaching course as D. The course D is divided into teaching units that are numbered by $d_1, d_2, ..., d_n$, where $d_i \in N$. Each teaching unit contains a particular set of key concepts that a learner should master. Each such set we will mark by U_i $(1 \le i \le n)$. For each teaching unit $d_i, (1 \le i \le n)$ we define the value $C_i \in N$ and is limited by $\theta \in N$, which describes its complexity. If the teaching unit d_i takes more time and efforts to master, than the teaching unit d_i then $C_i > C_j$.

Let's take $U = U_1 \cup U_2 \cup ... \cup U_n$, that is U is the whole set of key concepts in the course D. Now let's define dependency matrix $K = \{K_{ij}\}, (1 \le i, j \le n)$ of teaching units, where. If d_j depends on d_i then $K_{ij} = 1$, else $K_{ij} = 0$.

A teaching scenario is a sequence of teaching units $X = X_1, X_2, ..., X_m$, where m<n, $X_i \in D$ and $(\forall i \ne j) \Rightarrow X_i \ne X_j$.

The scenario X is acceptable, if every unit appears in it only once and a unit appears in the scenario sooner than those that depend on it.

Formally, the scenario X is acceptable if $(\forall i \ne j) \Rightarrow X_i \ne X_j$, and if for any pair (X_p, X_q), where $X_p, X_q \in X$, if p < q, then X_p teaching unit does not depend on X_q teaching unit (as matrix K states), $1 \le p, q \le m$.

Let's define the complexity of the scenario X as, $\sum_{X_i \in X} C_i(X_i)$ where $C_i(X_i)$ is the complexity of the teaching unit X_i.

For each (X_i, X_{i+1}) pair of the scenario X let's define the concept of distance $r_i(X_i, X_{i+1}), 1 \le i \le m-1$. $r_i(X_i, X_{i+1})$ is the number of those teaching units that the teaching unit X_{i+1} depends on after the learner has mastered the teaching unit X_i. Let's define

$$F(X) = \sum_{i=1}^{m-1} C_i(X_i) \bullet r_i(X_i, X_{i+1}) + C_m(X_m).$$

We will say that $X = (X_1, ..., X_m)$ acceptable scenario is better than $Y = (Y_1, ..., Y_m)$ acceptable scenario if $F(X) < F(Y)$.

$X = (X_1, ..., X_m)$ acceptable scenario is the best if $F(X) \to \min$. There may be several best scenarios; in that case we will just take one of them.

The sequence of knowledge of a learner we will denote as $Z = Z_1, Z_2, ..., Z_n$, where Z_i is a sequence itself and reflects which key concepts are learnt and which of them not in the teaching unit d_i. It can be either mastered $(Z_{ip} = 1)$ or not $(Z_{ip} = 0)$, Z_{ip} refers to the pth key concept of ith teaching unit.

Let's define the concept of teaching phase of a learner. It is defined in two steps:

- The best X scenario is being given to the learner. Testing is held after the learner has studied the units in the scenario X.
- Taking into account the results of testing Z vector and the matrix K are being updated to reflect the knowledge of the learner and the dependency between teaching units respectively.

Note here that each time when a learner passes a teaching phase the units, which have been included in the provided scenario and have been completely learnt by the learner (the corresponding Z_i sequence consists of ones only), are being removed from the whole teaching material thus removing the corresponding dependencies from K.

So, having defined the data domain of our problem let's state it formally. Build such a scenario X for each teaching phase, that $F(X) \rightarrow \min$.

Now let's depict the parameters of our problem into parameters that are meaningful in the GA. Teaching units will be the genes of the GA. Teaching scenarios will be the chromosomes of the GA. The set of teaching scenarios will be the population of the GA. If a teaching scenario is allowable then the corresponding chromosome is allowable as well. If the teaching scenario X is better than the scenario Y then the chromosome X is better than the chromosome Y in the GA.

There are many ways to solve this problem, but we have chosen the way that is provided by Genetic Algorithm. So, you may ask why GA? If GA can be used here then a regular algorithm may exist and possibly be better. Here we can answer, that the GA is used to optimize the problem. It is not used to find an exact solution. The problem itself is an optimization problem and it is hard to find a regular method for it. The GA guarantees that it will eventually find a good solution, because the GA has a "jumping" nature [George F. Ludger, 2003]. Mutating a chromosome or crossing over two chromosomes can yield much better chromosomes. Of course these operations can yield bad chromosomes as well. But the point to be considered here is that good chromosomes *are* constructed during the execution of the GA. And if we modify the GA so that it saved the best chromosomes after each cycle of its execution, we can be sure that in the end the GA will output the best result that it has found during its run.

The GA Problem and Its Parameters

A gene is represented as a whole number, namely it is the number of the teaching unit. Whole numbers are preferable here because it makes the logic of the GA easier [Z. Michalewicz, 1999], [George F. Ludger, 2003], and A.S. Hovakimyan, S.G. Sargsyan, 2005].

We have chosen *order crossover* and *double mutation* as the operations of GA [George F. Ludger, 2003].

Let's define the main concept of the GA, namely the fitness function for our problem. We will take $F(X)$ as fitness function for our problem. GA states that if X chromosome is better than Y chromosome if $F(X) < F(Y)$.

Here we can say that the chromosome X is the best if $F(X) \rightarrow \min$.

The Genetic Chooser Algorithm (GCA) Description

We assume that course author provides such information as the dependencies between the key concepts and the complexities of the key concepts. This kind of information will let us compute all the parameters of our problem.

For the beginning we assume that a learner knows nothing about the teaching material, and all the teaching units are still unstudied. Or the learner can take a test to find out his/her knowledge. If the learner knows nothing his/her vector Z is a zero vector. If the learner has taken a test and proved to know something, the corresponding elements of the vector Z will be set to ones.

Now let's describe the current step of GCA algorithm:
- Update the vector Z setting the members that correspond to learnt units to ones;

- Remove all the teaching units that are mastered. In this case some dependencies between the key concepts of the whole teaching material will disappear. If there is a key concept in a teaching unit which is not mastered that unit is not removed. Instead, its complexity value is decreased. The new complexity value is calculated by the following formula:

$$C_i'(X_i) = C_i(X_i) \bullet \frac{|U_i| - M}{|U_i|} + a$$

, where

- $C_i'(X_i)$ is the new complexity value, and $C_i'(X_i) < \theta$, $C_i(X_i)$ is the old complexity value, $|U_i|$ is the total number of key concepts in the teaching unit, M is the number of key concepts in the teaching unit that are mastered, a is a constant corrector value, $a < \min_i C_i(X_i)$. Its meaning is the following. If the learner has passed this teaching unit and the testing discovered that no key concepts are mastered, $M = 0$, it means that this teaching unit may be more difficult for this particular learner, and it is worth to have a higher complexity value.

- Having the updated vector Z, the new complexity values, the possibly decreased set of teaching units, run the GA for these input values.

- After the GA has completed its job and returned the best scenario, forward that scenario to the learner.

- Repeat all the steps mentioned above while the set of the teaching units is not empty.

Now let's detail what GCA does.

- Construct the matrix K taking into account the vector Z after testing,
- Construct the initial population of chromosomes,
- While the end-condition is not true do the following:
  1. Select some chromosomes (usually 1% of the entire population) using the roulette wheel method [Z.Michalewicz, 1999],[George F. Ludger, 2003],
  2. Order crossover the big part of the selected chromosomes,
  3. Double mutate the rest of the chromosomes,
  4. Check the offspring against acceptability,
  5. Compute the fitness values for all acceptable chromosomes,
  6. Add theses chromosomes to the population,
  7. Save the best ten (or other number of) chromosomes in a separate place.
  8. Throw away the worst chromosomes so that the entire number of chromosomes in the whole population remained the same.

Some aspects can be optimized. For example, a bad chromosome can contain a good "sub-chromosome" that is worth keeping around. For this purpose a "bucket brigade" algorithm is suggested to use [George F. Ludger, 2003]. The "end-condition" can be

- Completing some fixed number of cycles, or

- Testing if the difference between the average fitness of the previous population (the population before selection, order crossover, double mutation, and offspring addition) and the average fitness of the new population is small enough, or

- Testing whether the number of good chromosomes is big enough, etc.

Note that every time when testing is made the set of the teaching units are decreased. So we will eventually reach a situation when GA is neither good nor applicable because the set of teaching units is very small. In this case the "simple choosing" algorithm can be quite good (the fitness function is used here anyway to compare the chromosomes).

Having a set of chromosomes the GCA system gives another set of chromosomes where we can choose the chromosome which has the highest fitness value.

The GCA has been realized in the Java programming language. Experiments gave encouraging results. The entire GCA has been tested on hypothetical course with randomly generated dependencies between the key concepts. The test showed that the larger is the problem domain the better the GCA behaves comparing to the simple choosing algorithm.

The effectiveness of GCA also depends on the size of the population that the system operates on. The tests have shown that the larger is the population the better is the final fitness values. We can also see that the fitness value shrinks faster and faster but from some point it starts to shrink slower and slower. And there is some point where it stops changing. This also means that the best chromosome in of the final population is very close to the best chromosome entirely. See Figure 1.

L-systems in GCA

Having the matrix K (defined in section 2) we can construct the so called "dependency tree" of the entire material. That would be an oriented graph, where the nodes are the units of the teaching course, and two nodes are connected to each other if there is a dependency between them.

In the GCA system there is a support for showing the dependency graph of the course, which serves as a map for it. That map will be useful for a user to see the structure of the course.
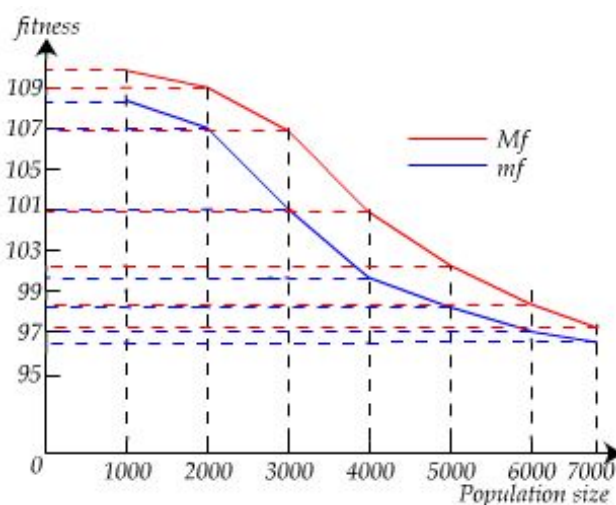

Figure 1

It is being updated with each passed scenario, drawing the mastered units with alternate color. This way a user can also see which parts he/she has passed and which parts still remain, which, we think is useful information for him/her. To actually draw this graph we have used the method of L-Systems [Jon McCormack, 2003].

This method suggests to have some starting formulas (axioms) and rules to be applied to them. Applying the rules to the axioms gives other formulas that we can apply the rules on, and get more formulas.

So having the matrix K and the starting point of the course we can draw the course map by the following way:
- Take a unit A, and all those units that directly depend on it. Let's mark them $B_1 \ldots B_m$.
- Draw oriented edges from A to $B_1 \ldots B_m$
- Do the first two steps until the entire course is considered.

Note that the *K* matrix that we will talk about through this section is the initial *K* matrix of the GA. GA changes it during its run, but we need to have the entire unit-dependency set in order to draw the course map, and note all those units that are already learnt.

Let's define the formal description of the steps brought above, that will help us to actually draw the map of the course. Let's define the basic elements for our L-system.

The alphabet is the following.

$$\sum = \{U_1, \ldots, U_n, >, [,], I, O\},$$

where U_i is the ith node-drawing action. ">"-marks the arrow-drawing action, "[" and "]" mark the "turn one unit left and push into the stack" and "turn one unit right and pop out of the stack" respectively, *I* and *O* mark the "change color" and "restore color" actions respectively.

Looking at the matrix *K*, find out all those units that do not depend on other units: i.e. the starting points of our course. Those units will be the axioms of our L-system. Thus

$$\omega \subset \{U_1, \ldots, U_n\}.$$

Any combination of symbols from Σ is called a formula. So axioms are formulas.

Let $CS = \{U_1, \ldots, U_n\}$, and *LS* is the set of learnt units. *LS* is constructed taking into account a learner's current knowledge vector Z (section 2).

The set *P* of production rules that are being applied to formulas of L-system is defined by the following way.

1. If unit U_i depends on U_j (as the matrix *K* states) and $U_i \in CS$, replace it with $[U_i > U_j]$, *CS* = *CS\Uj*.

2. For every $U_i \in LS$, replace U_i with IU_iO.

So $P = \{U_i \rightarrow [U_i > U_j], U_i \rightarrow IU_iO\}$.

Let's take $F = U_l \ldots U_p; (U_l \ldots U_p \in \omega)$ as the starting formula. Perform the rule 1 on *F*, while $CS \neq \varnothing$.

This way we will get the *course-map formula CF.*

Perform the rule 2 on *CF* while applicable. This way we get a learner's *knowledge-map formula* of the course *KF*.

Using *KF* the knowledge-map of a user is drawn. So a user can see his/her progress through the course with an alternate color.

Conclusions

In the presented article we discussed a problem dealing with the issues of the optimal management of teaching process in e-learning systems. This problem's aim is to construct such tools that adapt teaching materials to a user, which will allow the student to get knowledge effectively. We developed the GeneticChooser Algorithm (GCA) using the Genetic Algorithms' and L-Systems' concepts to solve this problem. We continue our researches in using GA-s and L-Systems in problems of developing e-learning systems and managing teaching process in them. The results we plan to present in our further papers.

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Authors' Information

SARGSYAN S. G. - *Department of Algorithmic Languages Yerevan State University 1, A.Manoogian str., Yerevan ARMENIA alglan@ysu.am*

HOVAKIMYAN A.S*. Department of Algorithmic Languages Yerevan State University*

1, A.Manoogian str., Yerevan ARMENIA, e-mail: ahovakimyan@ysu.am

BARKHUDARYAN S.V. - *National Academy of Sciences of RA 24, Bagramyan str.,Yerevan*

 ARMENI, e-mail: *Asergey@crrc.am*

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