

## An Intelligent Method for Customizable Adaptive Learning Content Generation

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**Abstract** - E-learning environments are being used more efficiently by the rapid growth in internet and multimedia technologies. Adaptive learning is a kind of learning environment which provides individual learning. It can customize the learning style according to the individual's personality and characteristics. Although there are a lot of e-learning systems having adaptive learning feature, they do not satisfy all adaptive learning aspects. This paper proposes a new method which tries to help learners find educational contents adapted to their personalities in an efficient manner. Our proposed method has four essential parts: 1) It finds out learner's features by MBTI and Kolb learning style tests or Bayesian networks. 2) Then It tries to select the most appropriate adaptive learning objects with 0/1 knapsack problem in a limited amount of time determined by learner. 3) An ant colony optimization algorithm is proposed to solve 0/1 knapsack problem efficiently. 4) Selected learning objects are then sequenced in order to preserve the prerequisites.

Also we created a software application based on this method called BehAmooz for learners to find and comprehend the educational contents effectively. The results obtained by experimentations showed that this method could satisfy most of the students.

**Keywords** - E-learning, Adaptive learning, MBTI test, Kolb test, Bayesian networks, 0/1 Knapsack, Ant Colony Optimization (ACO), Sequencing

### 1. INTRODUCTION

In traditional learning environments, teacher's experience plays an important role. In other word, learning is a process that the knowledge is created through transformation of experience [1,2]. So teachers try to transfer their knowledge to the learner by their own perception of the correct teaching methods. On the other hand, each individual has some characteristics and personalities which make him/her physically and

mentally unique [3]. Therefore the "One size fits all" approach may not suitable for all of learners [4,5].

Nowadays, by the rapid growth of advances in computer and network technologies, educational researchers have developed new methods, tools and environments for learning with the help of computers [6,7,8]. Hence, the term E-Learning environment appeared and used widely in education since mid-1990s. These systems can increase our achievement level on learning goals. However there are many E-Learning

systems which present the same educational content and pedagogical model to all of the users. The idea of optimizing these simple E-Learning environments by considering user's features and backgrounds brings out adaptive E-Learning systems [9]. So training and learning performance can be enhanced immensely by identifying the personal characteristics of learners and adapting educational content and its presentation to fit their demands more effectively [6]. These methods have wide impacts on the development of learning systems to have a dynamic learning process. This goal is pursued in adaptive learning and as a result, adaptive learning has attracted more attention in recent years [10,11,12,13].

Adaptive learning method tries to build a model from student's preferences, goals and interests and use this model to adapt E-Learning contents, pedagogical models and interactions between student and the environment to meet the needs of the student [14]. Two technologies have structured the adaptive E-Learning systems: (1) Intelligent Tutoring System (ITS) and (2) Adaptive Hypermedia System (AHS) [15,16]. This paper implements the adaptive learning with ITS technology.

ITSs are a kind of adaptive learning systems that apply artificial intelligence methods [16]. ITS attempts to simulate the teacher for the student to guide him/her through the pedagogical process. In this method a student model will be constructed and do the following tasks: (1) collect data from the student, (2) use the collected data to create a representation of the student's knowledge and learning process, (3) predict the type of student's response in the learning process, compare that prediction with the student's response and use the obtained data to refine the student model. In ITSs, AI methods are used to optimize the functionality of providing the adaptive contents to the student. AI techniques provide more flexible interactions with the system [17,16]. Researches on ITSs demonstrate that students who were taught by these systems learn faster with more performance compared to classroom-taught students. Researchers at Carnegie Mellon University developed an intelligent tutoring system called LISP Tutor to teach computer programming courses to college students. Students who used LISP Tutor scored 43 percent higher on the final exam than the students who attained at traditional classrooms. Aforementioned system also has an impact on the performance of learning. Given a complex programming problem, the classroom-taught students required 30 percent more time to solve the problem compared to the ITS students [16].

In this paper, we model the educational content generation to a knapsack problem and by solving that, we propose a new method for adaptive learning. The knapsack problem selects the elements which best fit the learner's needs and constraints. There are many ways to solve the knapsack problem but the ant colony optimization (ACO) has shown great results on this problem [18].

The remainder of this paper is organized as follows: In section 2, we briefly review related works. Section 3 presents our methodology. Section 4

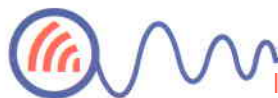
presents an application which has developed by the authors. Section 5 demonstrates our experimental results and evaluation of our method and finally section 6 provides conclusions and future works.

## II. RELATED WORKS

In the past decade, researchers of computer science and education were attracted to the field of applying adaptive learning through the pedagogical process. One of the features of an adaptive system is to highlight learner's preferences, interests and browsing behaviors to offer personalized services [19]. However, although the educational content must be suitable for the particular requirements of each individual, they have to be flexible enough to be used by a wide range of community of developers and learners [20]. Therefore, various methods were proposed to measure the learning styles and adapting the contents according to user's needs. Course Maintenance System, Adaptive Courseware Generation and Dynamic Courseware are the three main approaches [21] that have been proposed in this case and numerous systems have been developed based on them. In [22], the study introduced learner-difference profiles called learning orientations and the System for Intentional Learning and Performance Assessment (SILPA), an interactive Web learning environment, to investigate how individuals manage learning in environments designed to support learning orientations. Reference [23], describes the development of Hypermedia-based English Learning system for Prepositions (HELP), which provides EFL students learning diagnosis and remedial instruction according to student confidence scores (CR). Reference [24], selects the learning content based on learner's cognitive state, and presents learning content through selecting teaching media based on learner's learning style.

Snow and Farr (1987) tried to prove that sound learning and traditional classrooms are incomplete if they do not consider the students preferences. They implied that the educational programs cannot be successful without paying attention to the learner's needs [25]. The Comprehensive Application of Behavior Analysis and Self-sustaining (CABAS) was proposed in 1994 by F. S. Keller. In CABAS schools, the individualized instruction of each learner influences the behavior of the entire education community [26]. In 1998 Brusilovsky introduced Adaptive Hypermedia Systems (AHS) to support individual learning. AHS is based on adapting the educational content for each learner according to his/her profile. AHS should satisfy three criteria as follows: (1) it should be a hypermedia, (2) it should have a learner model, and (3) have the ability to adapt the hypermedia using the learner's model [4,27].

In the same year, G. J. Hwang proposed an online learning system. Several parameters were defined in this system to obtain the learner's features. For example idle time, response time, effective learning time, ineffective learning time and login time. Based on aforementioned parameters the system can detect various learning attitudes of the student, such as concentration, willingness and patience. So the system can



adapt the contents by considering the obtained results from the learner [28].

In addition, several methods have proposed on intelligent tutoring systems. Concept Map automatic construction (Tseng, Sue, Su, Weng, & Tsai, 2005) was developed and proposed a Two-Phase Concept Map Construction (TP-CMC) approach to automatically create the concept map by learners' historical testing records. Phase one is used to preprocess the testing records. Phase two applies multiple rule types to further analyze the mined rules and then proposes a heuristic algorithm to automatically create the concept map, based on the observation in real learning situation [29]. Juei-Nan Chen et al. presented a Dynamic Fuzzy Petri Net (DFPN) model to increase the flexibility of the tutoring agent's behavior. Based on each learner's behavior, the tutoring agent provides a different educational content and then maps it onto a SCORM activity tree structure [30]. Another method is a standardized course generation process by using DFPN which was proposed by Huang, Chen, Huang, Jeng, & Kuo. The platform was made up of MEAT (Mobile E-learning Authoring Tool), LRMS (Learning Resource Management System), ANTS (Agent-based Navigational Training System), and a material arrangement agent. The material arrangement agent adopts DFPN and the proposed extended model to introduce a process called SCGP (Standardized Course Generation Process). The generated multimedia course is interoperable, reusable, and standardized. Furthermore, the automatic process enables lecturers to efficiently generate courses [31].

Aforementioned methods and approaches have some great advantages and the outcome of their results was also acceptable. However, they do have some disadvantages. For example, they are not customizable enough. Learning style path cannot get enhanced and modified by teacher. Furthermore, some of them do not consider the learner's constraints while presenting the adaptive contents. For an instance, student's available time for learning may be limited. And finally, in some cases they cannot provide the most suitable adaptive learning environments all the time. Some approaches can get adapted with the learner over time. Therefore, at the first times of using those methods, contents are not adapted with the learner. In this paper we are trying to solve these shortcomings.

### III. METHODOLOGY

In this section different parts of the proposed method will be explained [32].

#### A. Structure of an educational content

There are various teaching materials (TM) in the context of an educational content, which instantiate different ways to teach the concept or the topic (e.g. introduction, explanation, examples, a help item, exercise or test) [21]. Each category of teaching materials forms a *group* of *elements* in the proposed method. So each TM falls in one of these elements groups, which we call it an element. Figure 1 demonstrates the relations between terms introduced above.

#### B. Adaptive learning

The goal of this paper is to select the elements which match with the learner's characteristics and features most. So we need to obtain learner's features and store them in a suitable structure (learner model) for further use. For this purpose, two approaches can be applied: (1) using learning style tests (2) applying Bayesian networks. In following, these two approaches are concisely reviewed.

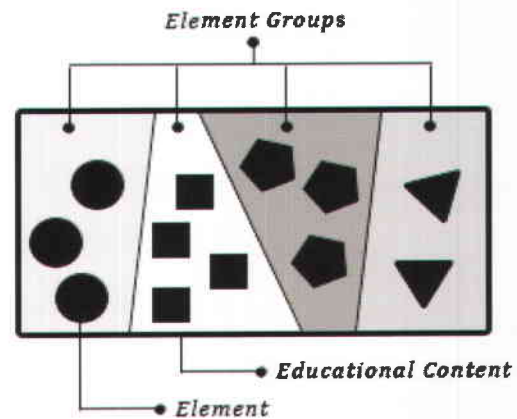


Figure 1. An example of relations between educational content, elements group and elements

#### 1) Learning style tests

In order to identify features of a learner accurately, we ask some questions from him/her. These questions are derived from two standard psychological tests, Myers-Briggs Type Indicator (MBTI) and Kolb, which are explained respectively as follows.

##### 1.1. Myers-Briggs Type Indicator

Myers-Briggs Type Indicator (MBTI) is one of the popular personality tests, based on Carl Jung's theory of psychological type. It classifies individuals in sixteen groups of personalities, based on their energy, information source, decision-making and life style [33]. This method can obtain the learning style of the learner which can then be applied on the learning process. MBTI test evaluates learner to obtain four features with two possible values for each one. Its results contain sixteen personality types (Table 1).

Table 1 . Different MBTI Personalities

ISTJ	ISFJ	INFJ	INTJ
ISTP	ISFP	INFP	INTP
ESTP	ESFP	ENFP	ENTP
ESTJ	ESFJ	ENFJ	ENTJ

We use this method for identifying the effective learning style parameters because: (1) these features were directly related to learning styles and the way students collect information [34]. (2) there were clear and standard question set and scoring system that make our results more reliable [35]. (3) Features of Jungian framework have been revealed to be independent [34]. So there would be minimum redundancy in our data collection.

In following, the features which can be obtained by MBTI will be described concisely.

- *Extraversion/Introversion:*



Extraverts get energy by communicating with people, involving in activities or interacting with things around them. Every impression for them has an expression. In fact they live in outside world [36]. During learning process, extraverts prefer to explain what they have just learnt to their friends. Because they feel assured about their knowledge, only after their presentation [37].

For introverts, unlike extraverts, ideas, concepts and abstraction are the things that absorb them and make them feel happy about the world. Actually they prefer living in inside world [37,36]. In learning process, introverts prefer to make an interconnection between different subjects and make a "big picture". Other knowledge out of this big picture is out of their interest and knowledge [37].

In this paper, we tried to give Extraverts many questions in order to force them explain everything they have learnt. For instance, if we teach them parts of human body, a picture or text to fill its blank parts would be helpful. And for introvert learners, helping them to form relationship between new lesson and previous lessons in their mind would be useful.

#### • Sensing/Intuition:

Collecting Information is different from one individual to another. Sensing people prefer to rely on real world and what they perceive by their five senses. They look for facts and trust them. Because the units of information in their minds are facts, they need them to be organized and reliable [36]. In order to teach learners with this characteristic, organization in different parts of the learning process is really important. In this way, we inform them clearly "What Must Be Known". Besides, it's preferable to use ATA (Application-Theory-Application) method in order to organize lessons [38]. This method forces them to challenge the problem, concentrate on it and get ready for accepting the facts and put facts in their right position.

On the other hand, intuitive people trust on their analysis and concepts. They look for relationships between facts and try to find patterns so that they can improve "big picture" which is in their mind. Intuitive students prefer TAT (Theory-Application-Theory) method rather than ATA, but it does not matter what type of organization to use for teaching. It is better to leave some gaps for their "discovery" [38,37].

In our system, we devised some contents like tables, maps and etc. to summarize concepts of related subjects in a comparative format for "S" type learners. We tried to force "N" type learners to generate these kinds of comparative elements and patterns by themselves. We use any kind of interesting audio-video related to the subject for "S" type learners. Due to the relationship between movies and voices to their senses, the learning process becomes easier for them.

#### • Thinking/Feeling:

After data collection, the process of decision making is different for each individual. Some people make decisions based on logic. However, others' judgments and decisions are based on their personal characteristics and feelings. In learning process, Thinkers like

struggling with formulas and logic statements. They prefer an impersonal environment that is full of cases for analyzing. However, feeling persons like to view subjects from humanity point of view. They prefer collaborative works. Therefore, teachers can attract them by an example from real life so as to involve them to the subject [37,38].

Due to our experimentation subject, we tried to teach words to "T" students, using word structures. Elements which remind grammatical structure of the word could be attractive for them. We tried to teach our lesson using human activities such as talking to "F" students. For example, using the word in suitable conversation would be a good way for teaching vocabulary to "F" type learners.

#### • Judging/Perceiving:

Judging people are always acting quickly either in making decisions or doing things. They only collect necessary data and not more. Perceiving people are always in the process of gathering data. They always postpone their jobs because it is never completed from their point of view [37,35]. A good way in teaching is to slow down the speed of "J"'s tasks by making them do some extra works on simple jobs and break a single project for "P"'s into smaller parts.

#### 1.2. Kolb learning style model

A learning style is a combinatorial description of ability, knowledge and experience that allows a person to do something in a perfect style. As time goes, an individual becomes more powerful in some of these skills and as a result, a learning style will be formed. David Kolb, Harvard professor of Organizational Behavior, defines learning style as "most comfortable ways to learn". In his words, learning style is influenced by combination of "perceive" and "process" of a person. In his experiential learning model, Kolb has joined the "perceive" dimension with "process" as another dimension orthogonal to "perceive" to form four learning styles: (1) Converger, (2) Diverger, (3) Assimilator, (4) Accommodator [9].

Perceiving spectrum has two ends: (1) concrete experience (CE) and (2) abstract conceptualization (AC). CE learners prefer to work in pairs and discuss with a partner. AC learners like to be taught under control of a teacher with a systematic approach.

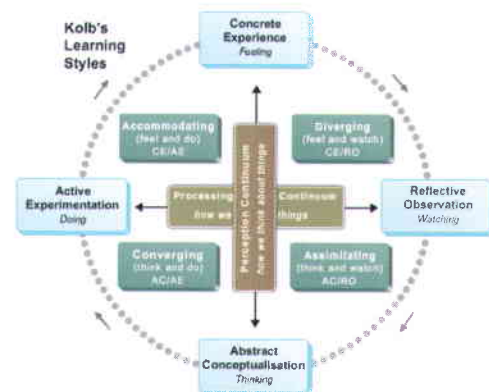


Figure 2 . Kolb's learning styles

Processing axis has two extreme points too: (1) active experimentation (AE) and (2) reflective observation (RO). AEs are active persons who make themselves involved in projects and practical assignments to learn something best. In contrast, ROs tend to carefully watch things and collect data through observation [39].

According to this classification, Divergers are people who learn something best if they view its different aspects. From four mentioned abilities (CE, AC, AE, RO) they dominantly have CE and RO. These people are interested in gathering information and have strong imagination and sensing powers. They prefer to work in groups.

Assimilators' abilities are mostly AC and RO. They rather concentrate on ideas and abstract concepts. Overall, assimilator individuals think it's more important for a theory to be logically sound rather than having useful applications. These people learn best by reading, exploring analytical models and having time to think about new issues.

Converging learners have strong AC and AE abilities. They find convenient and sensible applications for ideas and theories. While learning, they prefer to experiment or simulate procedures and do practical assignments in a laboratory.

Accommodating people are interested in new and challenging experiences. They dominantly have AE and CE features. Accommodators prefer to solve problems or work within a group of friends and test several approaches while doing a project [40,41].

To identify a person's learning style, Kolb has designed a questionnaire with 12 questions. We have used these questions to discover learner's features.

## 2) Bayesian networks

Although many of learner's preferences and features can be identified by MBTI and Kolb methods but in some situations the teacher may need to customize the learning style by his/her own. In other word, he/she may want to identify some features which cannot be obtained by previous mentioned learning style tests. Hence, an alternative method should be applied to determine those features. First of all learner's model should be obtained. However, one of the difficulties we face with is that modeling tasks involve a high level of uncertainty [42]. In order to overcome this issue, [42,43] has proposed a method that we use it in our paper. This method introduces how to use Bayesian networks as a unifying framework to manage uncertainty in learner modeling. We pose various questions to find out the learner's characteristics and features. These questions explicitly have been asked from learner. Another way is to recognize them in an implicit manner, considering the behavior of the learner in our educational environment. In the following we explain how Bayesian network works.

Bayesian network (BN) is a combination of two definitions of mathematical area [44]: probability theory and graph theory. The graphical model of Bayesian network is using directed acyclic graph (DAG). The nodes in BN represent propositional variables of in-

terest. The links of a BN represent informational or casual dependencies among the variables. These dependencies are quantified by conditional probabilities for each node given its parental nodes in the DAG. It allows us to compute the probability of a state of the variable given the state of its parent [44]. Figure 3(a) shows a simple Bayesian network.

Bayesian network is based on the Bayes theorem which is shown in (1).

$$P(a|b) = \frac{P(a,b)}{P(b)} = \frac{P(a)P(b|a)}{P(b)} \quad (1)$$

With the help of Bayesian networks, we make a learner model to show the relation between learner's characteristics and questions. In our method, each learner's feature has its own BN. For example in Figure 3(a),  $P(S_i)$  represents the presence probability of feature  $S_i$  in learner. These probabilities can be obtained from the statistics achieved by psychologists. Also we can use these statistics to indicate that, if the learner has the feature  $S_i$ , with which probability he/she can answer the question  $Q_{ik}$ . In this Bayesian network  $P(Q_{ik}|S_i)$  shows this probability ( $1 \leq k \leq m$ ). After evaluating answers of the learner to each relevant question,  $P(S_i)$  will be updated by following:

- If the answer was correct,  $P(S_i)$  will be increased.
- If the answer was incorrect,  $P(S_i)$  will be decreased.

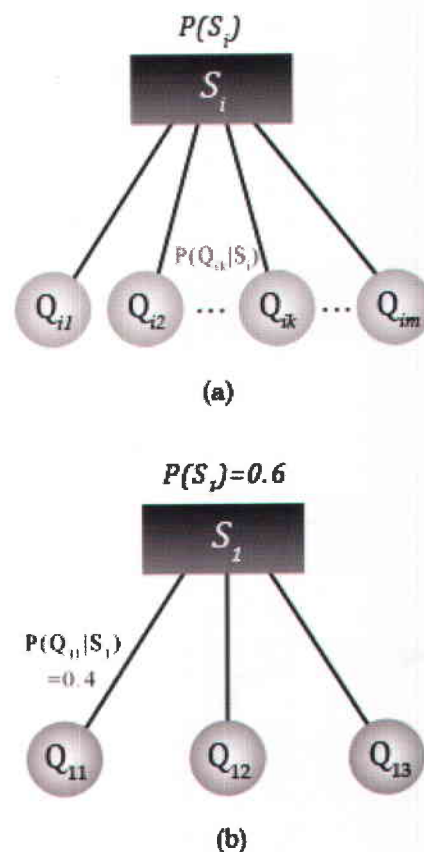


Figure 3 . (a) Diagram of the structure of a BN.  
(b) A sample of a BN.

$k_1$	$k_2$	$k_3$		$k_i$		$k_n$	
1	0	0	1	...	1	...	0

(a)

$k_1$	$k_2$	$k_3$		$k_i$		$k_n$	
0	0	1	1	...	1	...	1

(b)

Figure 5. (a) Elements' feature matrix  
(b) Learner's feature matrix

For example, in Figure 3(b),  $P(S_1) = 0.6$ . If the

learner answers  $Q_{11}$  correctly, the probability of having this feature will be updated by following:

$$P(S_1|Q_{11} = \text{True}) = \frac{P(Q_{11} = \text{True} | S_1) \times P(S_1)}{P(Q_{11} = \text{True})} \quad (2)$$

$$= 0.75$$

As we see,  $P(S_1)$  increased. But what would be the result if the learner selects the wrong answer to the question? By calculating the probability of  $P(S_1|Q_{11} = \text{False})$ , the result is 0.529. It is obvious that  $P(S_1)$  has been decreased. We do this process for every question related to this feature in order to obtain the final result.

Finally, we create a  $1 \times n$  binary matrix for each element to store the element's features. Each column in this matrix represents a feature. Entries of the matrix are only 0 or 1. If the value of  $i$ -th entry is one, it indicates that this element has  $i$ -th feature. For example, if an element simply, consists of a text, it's the best choice to be used for an Assimilator learner, because as we mentioned, an Assimilator can read the text and think about its subject to perfectly learn the topic. Consequently, the corresponding entry for Assimilator style in features vector of that text will be set. After evaluating learner's answers to questions and obtaining the learner's features, we create another  $1 \times n$  matrix to store learner's features in it. These matrices are illustrated in Figure 5. Now by comparing each element matrix with learner's feature matrix, we can obtain the accommodation of that element with the learner's features. Adding the entries which their value is one in both matrices forms a variable  $Pr_i$  which indicates the profit of  $i$ -th element for the learner.

### C. Selecting appropriate elements

In order to present the most suitable teaching materials to the learner in a limited period of time, we have applied 0/1 Knapsack problem. The 0/1 knapsack problem is one of the most famous combinatorial optimization problems. It is known as a classical NP-complete problem, which has extremely a large search space [45,46,47]. The 0/1 knapsack problem can be stated briefly as: given a finite number of objects and a knapsack, find the maximum total profit under the constraint that the total weight of all chosen objects is at most the weight limit [48,49,50].

#### 1) The formulation of the 0/1 Knapsack problem

The 0/1 knapsack problem is defined exactly as follows: We are given  $n$  elements and a knapsack. Element  $i$  has a weight  $w_i$  and the knapsack has a weight limit  $C$ . If object  $i$  is placed into the knapsack, we will obtain a profit  $Pr_i$ . The problem is to maximize the total profit under the constraint that the total weight of all chosen objects is at most  $C$ . So, the knapsack problem can be formulated as [51,49,52,53]:

$$\text{Maximize } z = \sum_{i=1}^n Pr_i x_i \quad (3)$$

$$\text{subject to } \sum_{i=1}^n w_i x_i \leq C, \quad x_i \in \{0,1\}, \quad (4)$$

$$i \in \{1, \dots, n\}.$$

Where  $x_i$  is a binary variable denoting whether object  $i$  is chosen or not. Equation(4) is the constraint that needs to be satisfied and equation (3) defines the profit of a feasible  $n$ -tuple. Figure 4 demonstrates the problem.

#### 2) Modeling proposed method to 0/1 knapsack

Now we try to model our element selection method to a 0/1 knapsack as follows:

Because of time constraints, learner determines his/her available time. This value is the total amount of time available to our teaching process. Each element group has an importance factor defined by the author of educational content. By considering this factor and total amount of available time, we can calculate the time needed for each element group. Obtained time is the constraint value of the knapsack and we define it as  $C_j$ .  $j$  indicates the  $j$ -th element group.

Each element has its own importance factor and difficulty. So the author must assign a pre-defined time needed to be studied by learner to each element. On the other hand learning speed and performance is not equal in every learner. To achieve learner's speed factor, the learner's speed in the system will be observed over time. The results of this observation are transformed to a coefficient. By multiplying this coefficient to each element's minimum time we can attain the time needed to study that element. Each

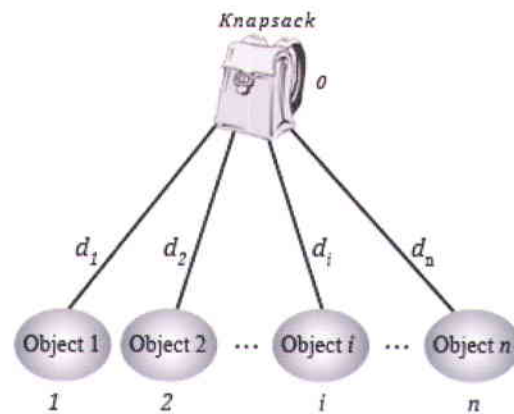


Figure 4. The description of a 0/1 knapsack problem



Element's time amount is denoted by  $w_i$  which  $i$  indicates the  $i$ -th element.

### 3) Using ACO algorithm to Solve 0/1 knapsack problem

As we mentioned before, 0/1 knapsack is one of the NP-Hard problems and has been thoroughly studied in the last few decades and several algorithms for its solution are available [53]. However classical methods for solving 0/1 knapsack problem usually face exponential computational complexities [18,51]. Ant colony optimization (ACO) algorithms are a class of algorithms inspired by the observation of real ants. Real ants are capable of finding the shortest route between their nest and food source through their biological mechanisms. Many search activities have been devoted to artificial ants, which are agents with the capability of mimicking the behavior of real ants [54,55,56]. Agents are capable of exploring and exploiting pheromone information, which has been left on the ground when they traversed. While building the solutions, each agent collects pheromone information on the problem characteristics and uses this information to modify the representation of the problem, as seen by other agents. With such concepts, a multi-agent algorithm called ant colony optimization has been widely used as a new search algorithm in optimization problems [18,57] like 0/1 knapsack problem.

In this paper, we used ACO algorithm to solve 0/1 knapsacks. The ACO method not only produces valid routes all the time but also yields better quality solutions [18]. ACO is a constructive population-based search algorithm to solve optimization problems by using principle of pheromone information. Several generations of artificial agents in a cooperative way search for best solution. The pseudo-code of ACO algorithm is stated as follows [18,54]:

#### **Procedure: Ant Colony Optimization**

##### **Begin**

**While** (ACO has not been stopped) do  
     *Solution\_Construction*();  
     *Pheromone\_Evaporation*();

**End;**

**End;**

Agents find solutions starting from a start node and moving to feasible neighbor nodes (*Solution\_Construction*). During this process, information collected by agents is stored in the so-called pheromone trails and agents release that pheromone while building the solution. To avoid locally convergence and to explore more search space, pheromones will evaporate. *Pheromone\_Evaporation* is a process of decreasing the intensity of pheromone trails over time.

In [18], method of solving 0/1 knapsack problem has been described in detail. Suppose that we are given  $n$  elements and a knapsack. Node 0 denotes knapsack and node 1 to  $n$  denotes elements. See Figure 4 for clearance. The distance between node 0 and  $i$

( $i \neq 0$ ) is indicated by  $d_i = w_i/p_i$ . The first term is node zero (knapsack) and then it is to find the next node with the constraint that each node is allowed to be visited once. The representation of  $d_{ij}$  is encoded as a matrix of activities. Then  $d_i$  is the  $i$ -th node in the array corresponding to the  $j$ -th node activity. The cost of the tour is the total distance traveled, and the total profit can be found under the constraint that the total weight of all chosen objects is at most the weight limit  $C_j$ . Agents decide to travel from node  $i$  to node  $j$  by following:

$$\pi(j) = \begin{cases} \arg\{\max_{i \in allowed_k(t)} [\tau_{ij}(t) \cdot \eta_{ij}^\beta]\} & (q \leq q_0) \\ S & \text{otherwise} \end{cases} \quad (5)$$

where  $\eta_{ij}$  is the heuristic information and is set as the highest value of  $d_j(\eta_{ij} = 1/d_j)$ .  $\beta$  is a parameter representing the importance of heuristic information,  $q$  is a random number uniformly distributed in  $[0,1]$ .  $q_0$  is a pre-specified parameter ( $0 \leq q_0 \leq 1$ ).  $allowed_k(t)$  is the set of feasible nodes currently not visited by agent  $k$  at time  $t$ , and  $S$  is an index of a node selected from  $allowed_k(t)$  according to the probability distribution given by:

$$p_{rs}^k(t) = \begin{cases} \frac{\tau_{rs}(t) \eta_{rs}^\beta}{\sum_{u \in allowed_k(t)} \tau_{ru}(t) \eta_{ru}^\beta} & \text{if } s \in allowed_k(t) \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

In finding feasible solutions, agents perform pheromone updates as follows:

$$\tau_{ij}(t+1) = (1-\psi)\tau_{ij}(t) + \psi\Delta\tau_{ij} \quad (7)$$

where  $0 < \psi \leq 1$  is a constant.  $\Delta\tau_{ij} = Qw_jx_j$  and is a positive integer.

Finally, this algorithm is repeated until the best solution is met. Attained solution is a set denoted by  $X = \{x_1, x_2, \dots, x_n\}$ .

#### **D. Sequencing selected elements**

Hitherto, we selected the most appropriate elements considered by the learner's feature. However representing these elements to the learner without any sequence is not a wise solution. In fact, teaching materials included in an educational content are often related to each other. In other word, this is not possible to comprehend a TM without any background of related TMs and it obviously has bad effects on learning quality. So we need to:

- Consider the possible dependencies between selected elements from knapsack in order to preserve the cohesion of the educational content.
- Make a decision on selecting or deselecting the elements which their dependencies has been violated.

In order to achieve these goals, we store these dependencies in a Directed Acyclic Graph (DAG). This graph is denoted by  $G = (V, E)$ .  $V$  is the set of all elements in educational content. We define a coefficient  $\beta_i = \frac{Pr_i}{w_i}$  for each element included in  $V$ . Now for the elements which are prerequisite for our selected ones but not selected, we must decide on add



these elements to selected ones or not. So for each of these elements formula below will be calculated:

$$x_k = \frac{\sum_{i \in \text{selected\_descendent}(k)} \beta_i}{\sum_{i \in \text{descendent}(k)} \beta_i} \quad (8)$$

Where *selected\_descendent(k)* is the set of selected elements and descendent of element *k*. *descendent(k)* is a set and contains the descendent elements of *k*.  $x_k$  is a number in  $[0,1]$ . By comparing  $x_k$  with  $\alpha$  (a pre-defined parameter which is distributed in  $[0,1]$ ):

- If  $x_k < \alpha$ , all descendent elements of *k* will be omitted. Because element *k* is prerequisite for its descendent.
- If  $x_k \geq \alpha$ , element *k* will be added to selected elements.

$\alpha$  is a pre-defined parameter and distributed in  $[0,1]$ . Finally, we compare the total  $w_i$  of selected elements with the total amount of time defined by learner. If it has a noticeable difference,  $\alpha$  will be changed and the decision will be made again.

Hitherto, we have a DAG which has tree-like structure. So we can traverse it level by level (like breath first search) and choose each visited element in final content.

#### IV. APPLICATION

In this section, we illustrate how we have used the explained method to develop an adaptive learning application called BehAmooz. This application is a standalone version of our software. BehAmooz consists of different modules which are implemented as classes in our framework. The general architecture of BehAmooz was shown in Figure 7. In the remainder of this section we will explain general parts of this architecture concisely.

##### A. Registration

Each new user must register to be able to use BehAmooz. After the completion of registration process, the student will take a learning style test (See Figure 6). This test is added by teacher using Test Management module. The software uses student's responses to obtain his/her features. These results will be used

for generating appropriate content for this student as discussed earlier.

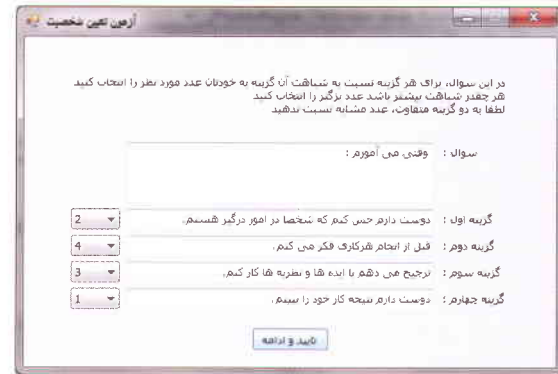


Figure 6. Screenshot of learning style test

##### B. Test Management

Since each test can reveal just some of student features, so we need a module to manage learning style tests. The teacher is able to add new tests and questions based on learning needs of that specific topic. As a default test, MBTI and Kolb tests are added to BehAmooz, but this software is flexible enough for any test.

##### C. Content Management

The teacher is responsible for adding sufficient teaching materials for each topic (See Figure 9). For each topic teacher can add/edit groups of elements and add/edit elements which are in that group (See Figure 8). He/she is expected to determine the base time needed for each element to be learnt. Also, teacher should specify which feature is affecting the learning of this specific element. Then the teacher should set importance rate of each group for each topic. On the other hand, the teacher is the best person who knows possible dependencies between elements. So we expect him/her to determine these dependencies too.

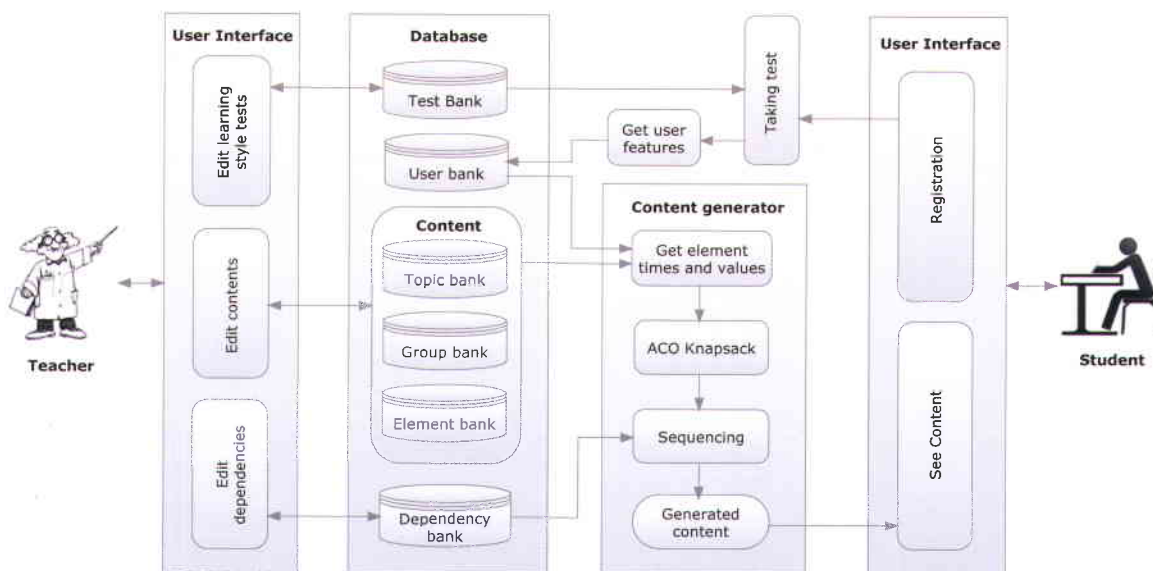


Figure 7. General architecture of BehAmooz





Figure 8. Screenshot of groups and elements

#### D. Content Generator Engine

This module will select appropriate elements for the current user and show these elements to him/her. To achieve this goal, it gets all elements for a selected topic and runs ACO Knapsack module to get preferred elements for the current user. Then based on the dependency tree that is defined by the teacher, content generator engine is able to decide on sequence of selected elements and present final contents to the student.

#### V. EXPERIMENTAL RESULTS

We tried to observe the functionality and efficiency of the BehAmooz tutoring system in real world. So this software tested by 46 students from four different schools and educational institutions. A survey was devised to evaluate the software from different aspects. This survey contained 10 questions which each one has 5 points (Table 2). It was given to all of the students who tested our software and the results are as follows.

The result of the survey and also the feedbacks of the students were significant. Figure 10 demonstrates the evaluation of BehAmooz from viewpoint of students. As it is shown, BehAmooz has a great impact on the learning path of the students. In Figure 10, the

graphic bar indicates the average score for each question. We will analyze each graphic bar value to explain our achievements.

Questions 2, 4, 6 and 9 (Table 2) are related to efficiency of our method. 79 percent of the students could finish their study in the time limit specified by themselves. Only 7 out of 46 students ran out of time limit. It was due to lack of concentration and unfamiliarity with the system. Those students showed better results while interacting more with BehAmooz. It means that the 0/1 knapsack and ACO algorithm are capable enough to limit the content according to learner's available time. Quality and cohesion of the contents proposed to the student can be evaluated by the results of questions 4, 6 and 9. About 67 percent were satisfied with cohesion and sequence of the teaching materials. It can get improved by optimizing the sequencing section of BehAmooz. However, time limit and amount of contents affect this factor.

Outcome of the sixth question was really important for us. This question evaluates our main goal throughout this method. It has direct relation with adaptive learning. About 84 percent of students were excited by the contents proposed to them by BehAmooz. Figure 11 illustrates the proportion of students who scored this question between zero to five. 30 students were totally satisfied by the system and scored 5 out of 5 in the survey. In conversations we had with them, participants said that the contents were so close to their needs and they did not feel bored or frustrated while studying. This result is a proof for efficiency of this method. Accordingly, it is obvious that in this educational environment, students learn better and perceive more accurate.

Result of third question is not as significant as others. Students still need to keep in touch with someone who guides them and interact with somebody who is in real world. This result may be possibly caused by students' previous perceptions from E-Learning systems. Adding some facilities such as

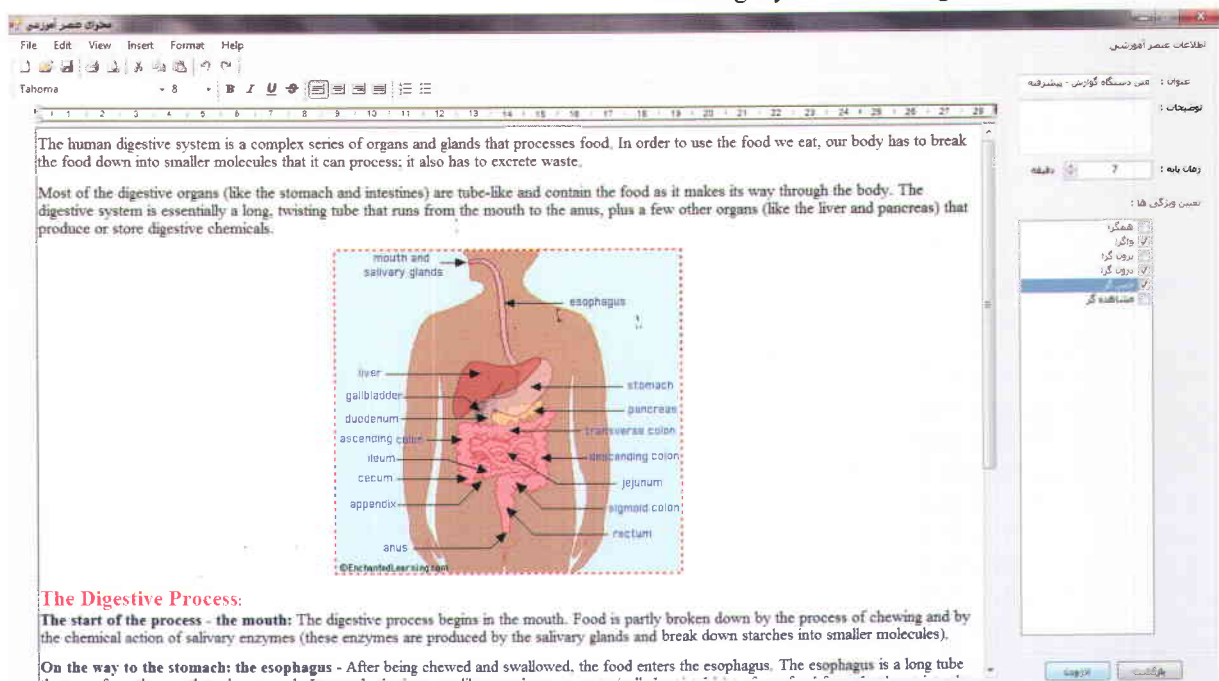


Figure 9 . Screenshot of adding an element

Table 2 . List of survey's question to evaluate proposed method

Question to ask	Maximum Points
1 Did you read or see all the contents provided by the software?	5 points
2 Did you finish your study in the time you specified at the beginning?	5 points
3 Did you need to have a teacher or a person who can help you through the study or you was self-learning all the time?	5 points
4 How much the contents was sequenced and related to each other?	5 points
5 Do you want to use this software in other courses?	5 points
6 Did the learning path and contents related to your needs and preferences?	5 points
7 How much did you interested in learning by using this software?	5 points
8 Do you think that this software shorten your learning process?	5 points
9 Do you think that you have understood the entire learning subject?	5 points
10 If you have used other E-Learning software before, do you prefer to use this software (BehAmooz) again?	5 points

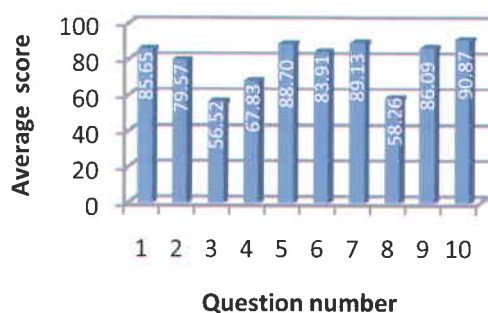


Figure 10. The result of survey according to each question

speech recognition in order to empower the learner to interact with the software by voice and thus increase his/her involvement and decrease the need to have someone to guide him/her, was a piece of notable advice from students.

Question 5 and 10 was designed to get informed by the comparison of BehAmooz with other E-Learning environments. As it is shown, about 90 percent of the students were satisfied by the overall performance of the system and wanted to use this method in their courses. They said that they feel more comfortable with this learning style while they did not have this feeling with other E-Learning environments.

Finally, to summarize the results, it is clear that this method proved that it can reach to its adaptive learning goals.

#### VI. CONCLUSION AND FUTURE WORKS

Using adaptive learning in learning environments is one of the useful approaches in education systems. In the traditional learning systems, the problem is that, during the learning process learner faces with a massive amount of contents while he/she has a limited time. Also some of the contents may not fit to the learner's needs. As a result, he/she may feel frustrated and disappointed. In this paper we tried to overcome this issue and produce optimized educational contents which satisfy the learner's actual needs by considering his/her personalities and features in a limited amount of time. A tutoring application has been developed by authors of this paper to provide a practical approach to our method. This software named BehA-

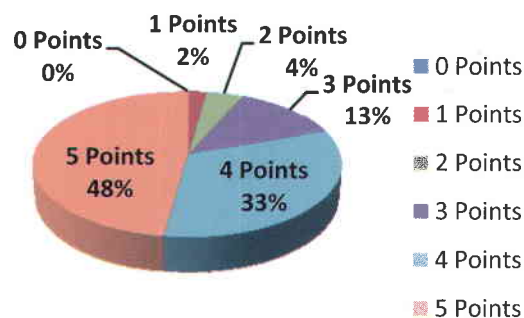


Figure 11. Result of sixth question

mooz, was tested by a group of students and the efficiency of our method was evaluated. The results indicated that the proposed method has the capability of providing a suitable adaptive learning environment.

Our future work will be on applying machine learning methods beside of learning style methods to sustain the changes of learner's needs. Another work will be done on designing and developing a learning web-based portal based on the BehAmooz application. It can help us to analyze the results more accurately.

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