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Personalized Courseware Construction using Association Rules with Differential Evolution Algorithm

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Abstract - The learning style of individual students differs from each other. Hence the common way of teaching a course for all the students with same course material, in the existing education system, becoming unsuccessful for the present generation of student community. As a solution to this problem constructing different courseware based on the learning style of the students is an open and challenging research problem. This paper proposes an approach for personalized courseware construction by integrating the Evolutionary Computing (*EC*) approach with a Data Mining (*DM*) technique. This proposed approach uses Differential Evolution (*DE*) algorithm for generating association rules for student learning style models so that relevant materials can be provided for the courseware based on the students' requirements and interest. The sample data from Felder-Silverman learning style is used for forming rules using *DE* to extract useful information for courseware recommendation. This paper presents this proposed approach in detail.

Index Terms – Personalized Learning, Courseware Construction, Association Rules, Differential Evolution, Learning Style.

I. Introduction

Educational Data Mining (*EDM*) is a widely researched field due to the immense number of problems in educational environment and the different possibilities of data mining solutions involved. *EDM* uses the modern computational techniques to solve the classic scenarios in educational field. Since the data mining field is a major area of research, its utilization for solving educational questions has become an increasingly emerging application. Evolutionary Algorithms (*EAs*) are a classic optimization tool, in *EC* field, used to solve data mining problems in different cases. These algorithms have been found to have great efficiency and stability in different data mining problems. Their usage for *EDM* has been limited but steadily growing. The *DE* algorithm is one of the simple and robust *EA*.

Nowadays, for educational courseware, it has become increasingly important to know about each student's requirements and the kind the learning materials suitable. The courseware authors have to be aware about the students' learning style so that he/she can include relevant material in the courseware. A student learning style modeling tool which includes puzzles, games and questionnaires has been proposed in [1] to derive the learning styles of students who are attending a course. It provides scores for different learning styles based on Felder-Silverman learning model. By using the data provided in the learning style models of [1], this paper proposes an approach to recommend the types of materials to be included in the courseware for a student. *DE* algorithm is used to mine association rules from the data provided. These rules are then used to recommend suitable materials for the courseware.

Based on the knowledge and societal factors of a student, his way of learning something varies from others. Each student follows their own way of learning. In the literature of educational data mining related studies the commonly seen learning styles (Visual, Verbal, Active, Reflexive, Sensitive, Intuitive, Sequential and Global) are identified and reported. According to the leaning style the students are classified as Visual Learners, Verbal Learners, Active Learners, Reflexive Learners, Sensitive Learners, Intuitive Learners, Sequential Learners and Global Learners. The different type of learners along with the details of their learning styles is presented in Fig. 1. In our experiment, the learning style analysis is done for 24 students of a Post Graduate class in our university. Each student was allowed to use the Student Learning Style

Modeling tool, and their scores for each learning styles are obtained.

Learning Styles	Different Learners	Description
Visual Learning	Visual Learners	Remember what they see like photos, diagrams, time tables and animation etc.
Verbal Learning	Verbal Learners	Remember what they learn, write and hear. For example: Book lovers.
Active Learning	Active Learners	Interactive personalities. The one who rises question or answers the question in: discussion, consideration, application, etc.
Reflexive Learning	Reflexive Learners	Reflect the information what they have heard or learnt. Prefer to work alone.
Sensitive Learning	Sensitive Learners	Patient learners, who believe in real life experiments, rather than facts. Don't like to complicate things.
Intuitive Learning	Intuitive Learners	Believe in theories. More interested in solving complicate problems.
Sequential Learning	Sequential Learners	Perfect understanding when gone through the material in stepwise process.
Global Learning	Global Learners	Dynamic learners. No connection is seen in their learning process

Fig 1.Different Learning Styles.

II. BACKGROUND STUDY

The objective of our survey was to identify different Evolutionary Algorithms which are used for Educational Data Mining researches and to identify a unique and novel problem that can be dealt and showcase the robustness of the *EA* being employed for the application. It is observed from our study that the four main factors that affect in any *EDM* problem are task, user, data mining technique and *EA* algorithm. The survey showed that the research works in construction and maintaining courseware is one of the crucial tasks and only a minimum work had been done in that line [2]. *EA* has many instances and out of all, *DE* is found be a very robust optimization tool. *DE* is also known for its simplicity in implementation. The performance of *DE* is still being improved through different research works [3, 4].

A sample rule generation was performed with the help of the data mining tool *KEEL* [5], using genetic algorithm in [6]. Alatas [7] employed a technique of producing association rules using *DE* algorithm for multi-objective optimization problem. Based on the literature survey the identified research gap is to propose *EA* based solutions for courseware construction for personalized learning. Hence, this papers proposes a system for "*courseware construction for course authors, using association rule mining and Differential Evolution algorithm*". Student Learning Style Modelling database (provided in [1]) provided necessary data for *DE* to generate association rules. Based on the association rules generated, suitable study materials are recommended for courseware construction.

III. METHODOLOGY

The methodology involves evolutionary derivation of association rules and the recommendation of the course materials based on these rules. The architecture diagram of the proposed approach is shown in Fig. 2.The system is implemented in two parts:

- **Association rule generation**

  This involves the pre-processing the database and based on this database mining the rules using the *DE*. The *DE* algorithm involves creating random rules from the database and improving/generating new rules based on different fitness measures available for association rule mining.

- **Courseware Structuring**

  This involves analysing the rules obtained from the *DE* algorithm, finding the strongest rules from the final population. Then based on the identified rules, the types of materials that can be included in the courseware are recommended.

IV. ASSOCIATION RULE GENERATION USING DIFFERENTIAL EVOLUTION

The structure of *DE* includes the following components: individual representation, population initialization, mutation, crossover, selection, fitness function and termination condition. The detail of each of component is explained below.

A. Individual Representation

An individual in the population is an association rule produced randomly based on the values of variables used in the Student Learning Style Modeling database. The maximum number of parameters that can be involved in a rule is decided base on the number of decision variables (d) required for *DE* for generating association rules. Hence each individual in the population consists of d tuples. Each tuple consists of four parts. The first part of each tuple represents the antecedent or consequent of the rule and can be either '*0*' or '*1*' or '*2*'. The value '*0*' and '*1*' means this item is in the antecedent and consequent part of the rule, respectively. The value '*2*' means this item is not a part of the rule. Hence, all tuples with the first value as'*0*' and '*1*' forms the antecedent and consequent part of the rule respectively. The second part of a tuple represents the learning style (the learning styles are numbered from 1 to 8). The third and fourth parts represent the lower bound and upper bound of the item interval, respectively. These bound are calculated separately by measuring the learning style of the individual students of a class and averaging their scores for individual learning style.

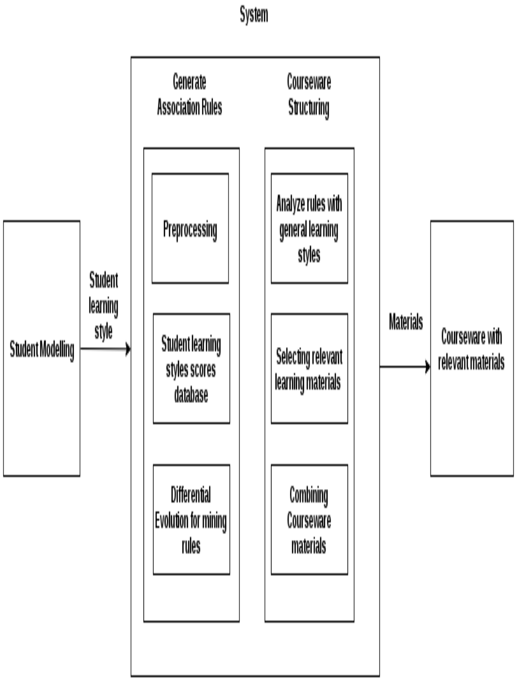

Fig. 2. Architecture diagram for courseware construction

For example, the individual, [[0, 1, 1.25, 3.59], [1, 5, 2.51, 4.43], [2, 3, 1.57, 2.56]] represents the rule:

IF "intuitive" value="[1.25, 3.59]"
THEN"reflex" value="[2.51, 4.43]"

In the first tuple of the individual, “0” represents that it is antecedent of a rule, “1” represents the learning style “intuitive”, and “1.25” and “3.59” indicates the lower and upper bounds of the respective learning style. In the second tuple, “1” represents that it is the consequent and “5” represents it is “reflex” learning style. The “2” in the third tuple indicates that it does not appear in the rule.

B. Initial Population

The initial population is created by assigning random values which lie inside the feasible bounds of the learning style to each decision parameter of each individual of the population as shown in the following equation:

$$I = Vmin + rand * (Vmax - Vmin) \quad (1)$$

where, I is the Individual, V_{min} and V_{max} are the lower and upper bounds of the variable, and *rand* produces a random real number between 0 and 1. Thus $rand * (V_{max} - V_{min})$ gives a random number between the given range. Therefore, in the case of learning style an integer random value between 0 and 7 is produced and for lower bound and upper bound a number between 0 and 5 is produced.

C. Mutation and Crossover

Mutation and crossover operations are for generating new and better individuals for the population. Mutation rate, F and crossover rate, C_r are used to improve the reproduction. These values are dependent on the problem in question and values are varied accordingly. For our experiment the F and C_r values are taken as 0.3 and 0.9, respectively.

During mutation, three individuals, r_1, r_2 and r_3 are selected from the population. The mutated individual (V) is generated using the Equ (2). For each individual (I) in the population a mutated individual (V) is generated.

$$V = V_{r_1} + F * \left(V_{r_2} - V_{r_3}\right) \quad (2)$$

Crossover is the next process in reproduction. Based on the crossover rate, crossover is performed. If the probability to perform crossover is greater than crossover rate, crossover is carried out. The crossover is performed between an individual (I) and its mutated individual (V), to produce a new individual. Each value in V is subtracted with the corresponding values in I, and multiplied by the specified mutation rate. This new individual is then added as a new rule.

D. Selection

Selection is the process of comparing the old and the new individual obtained after reproduction and choosing the better individual. In order to perform selection, fitness of current and new one in next generation, $V_{(G+1)}$ is estimated.

If $f(V_G) >= f(V_{(G+1)})$
$V_{(G+1)} = V_G$
Else
$V_{(G+1)} = V_{(G+1)}$

E. Fitness Function

Fitness function is used to find the strength of an individual, i.e., whether the individual is fit enough to be proceeded to next generation. Fitness function used in this context is the confidence measure of an association rule.

Consider the rule $X => Y$.

$$Support(X) = \frac{Total\ transactions\ in\ which\ \ X\ appears}{Total\ number\ of\ transactions} \quad (4)$$

$$Confidence\ (X => Y) = \frac{Support\ (X \cup Y)}{Support\ (X)} \quad (5)$$

For example, to find the support and confidence of the given rule:

IF “active” value = “[0.27, 1.45]”
THEN “sensitive” value = “[0.85, 2.60]”

Support of active learning style is the ratio of count of students who have the score within the specified range and the total number of students. The *confidence* of the given rule is obtained as the ratio of the number of students whose active learning style score and sensitive learning style score are within the specified ranges and the support value of the active learning style.

F. Termination Condition

The termination condition given is to repeat the process until the fitness measure of all the rules reaches the maximum, i.e., 1.0. Different numbers of rules were obtained during the process. Two sample rules are shown below.

IF "active" value = "[0.27, 1.45]"
THEN "sensitive" value = "[0.85, 2.60]".
IF "sequential" value = "[0.09, 3.67]"
THEN "sensitive" value = "[1.07, 3.73]".

V. RESULTS

The values of eight learning styles where obtained from the Student Learning Style Model [1]. Using this data, association rules were formed by *DE*. These rules are used for deciding the content of a courseware (as explained in Section 6). The courseware works in a way where the students, after taking the learning style modeling tests, are recommended with the appropriate course materials based on the scores procured. Given the following association rule, the inference which can be derived is:

IF "sequential" value = "[0.09, 3.67]"
THEN "sensitive" value = "[1.07, 3.73]".

If students have sequential learning style between the specified ranges, these students can be provided with sensitive learning style materials. The students who are sequential learning style follow a stepwise logical approach in problem solving. They are also sensitive which implies they depend on tried and true methods and formulas.

It was inferred from the data used, that 16 of the 24 students have the sequential learning style score within the specified range. These students also were found to have their sensitive learning style within its specified range as given in the association rule.

IF "visual" value = "[1.02, 2.67]"
THEN "active" value = "[0.65, 2.24]".

It was found that the students who have score for visual learning style between the given ranges are also active learners. These students tend to learn using figures, diagrams, images, etc. These students also tend to learn with experimentations. There are 7 students to have their two scores both in the ranges. These students can be provided with the learning style materials.

IF "active" value = "[0.27, 1.45]"
THEN "sensitive" value = "[0.85, 2.60]".

Students with active learning style score range in the specified range tend to be sensitive learners. These active students learn with the help of diagrams, images, figures. The sensitive students rely on formulas and equations to solve the problem. For the given sample data, these students are correlated so that the students within the learning score range can be recommended the appropriate course materials.

VI. COURSEWARE RECOMMENDATION

The paper proposed by Franzoni[8] describes a Learning Style to Course Material relationship which describes various learning materials based on different learning styles. With the knowledge of learning style, relevant course materials can be selected for the courseware by the course authors. In our experiment the association rules generated by *DE* and the Learning Style – Course Material relationship matrix are used to construct the recommended courseware for an M.Tech class with 24 students. The constructed courseware for this class is shown in Fig. 3. Based on the learning style analysis of the class the different kind of materials to be included for the courseware are pictures, graphics, slideshows, wikis, videoconference, web pages, videos and animations, online sources, forums and ebooks.

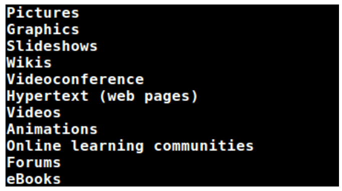

Fig.3. Learning materials recommendations based on rules generated by the Differential Evolution algorithm.

VII. CONCLUSIONS

This paper implemented an approach to integrate *DE*algorithm with association rule mining technique to construct courseware for the students based on their learning style. The data obtained from the Student Learning Style Model was used to obtain association rules using *DE* algorithm. The proper mutation and cross over rates were decided to obtain the most optimum results. The results were used to decide the type and content of the course materials for the courseware construction based on the Learning Style – Course Material relationship. The generated rules were verified manually with the sample data obtained from the M.Tech (Computer Science and Engineering) class with 24 students in our university.

This work can be extended further on validating the approach for larger set of students with diversified learning styles.

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