EAI Endorsed Transactions
on Energy Web
Research Article EAI.EU

Predicting Instructor Performance in Higher Education Using Intelligent Agent Systems

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Abstract

The arrival of information and communication technology is increasing due to growth of World Wide Web. Predicting the instructor's performance using the teaching style and their student's profile is a challenging issue in the education field. Several studies have been conducted to improve the student's quality by following dynamic contents. Ant Colony Optimization (ACO) is being widely studied by the researchers to optimize the quality of the educational content. This paper researches on predicting the performance of instructors using their teaching attributes. Initially, the profile of the student and the teaching attributes are designed to form the teaching route. Ants as intelligent agents such as filtering agent and a teaching path agent were designed. Experimental results have shown the efficiency of the proposed model. Finally, we discover that the certain set of knowledge like resource efficiency, updated knowledge, positive approach and well –planned teaching models plays a vital role to predict the instructor's performance [RA-7] .

Keywords: Communication Technology, Educational site, Intelligent agents, Teaching route and Teaching Quality.

Received on 22 April 2020, accepted on 14 May 2020, published on 15 May 2020

doi: 10.4108/eai.13-7-2018.164584

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1. Introduction

Thought to be a standout amongst the most critical needs of each subject, current social orders group training, which assumes a key part in the advancement of any nation [4], as an essential right of the general population. All through history, training confronted various difficulties and perspective changes. These days, administrators and establishments are worried about holding understudies and making picking up fascinating, proficient and powerful. Guardians, thus, are focus on understanding kids' execution and helping them with learning. Instructors and instructors need to comprehend the genuine circumstance of the educating learning process, with precise data that may direct and make an incentive through learning. At long last, understudies need to learn. Notwithstanding the difficulties and patterns uncovered above, [3] depict that the way to progress is incorporating understudies with present day mechanical changes and developments. They clarify that it is important to acquire incorporated and exact data (interior and outside to the school) of understudies keeping in mind the end goal to give guardians, instructors and school directors with the sufficient comprehension to help the basic leadership process that will coordinate the educating and learning exercises, which will most likely be diverse for every understudy.

Operators are propelled apparatuses individuals use to accomplish diverse objectives and to different issues. The principle distinction between conventional devices and specialists is that operators can work pretty much autonomously from the individuals who appointed office to the specialists. For quite a while people utilized just other individuals and at time's creatures as their operators [3]. Savvy operators shape a reason for some sorts of cutting-edge programming frameworks that consolidate fluctuating procedures, various wellsprings of area learning, and an assortment of information composes. The wise operator approach has been connected broadly in business applications, and all the more as of late in medicinal choice emotionally supportive networks [4, 5] and environment [6]. In the general worldview, the human chief is thought to be an operator and is consolidated into the choice procedure. The general choice is encouraged by an undertaking chief that appoints subtasks to the proper specialist and joins the ends come to by operators to frame an official conclusion**.** The rest of the paper is organized as follows: Section II presents the related work; Section III presents the proposed work; Section IV presents the experimental results and analysis and finally concludes in Section V.

2. Related Work

This section presents the existing mechanisms of our research study. Adaptive learning systems are mainly expressed and programmed nowadays. With the help of past information, the learner's behaviors are predicted under the class of supervised or unsupervised. Mostly, machine learning techniques are widely used for predicting the teachers and student's performances. A bi-layered structure formed to predict the performances. Depends upon the relevancy of the course, the performance of the student will be increased. Only when the student performance increases, the performance of the teacher can be evaluated. Decision tree, artificial neural networks and probabilistic algorithms were used for predicting the performances. Predictors are mainly classified into academic, demographic and psychological categories [7]. Maximum Weight First Order Derivation is suggested for validating the selected features. In order to eliminate the validation error, the cross-validation method is used for selecting the features. Investigate instructors according to the non-instructional factors, such as physical attractiveness and psychological factors [2][RA-4].

Emotional response agent is a sort of prediction agent that purely depends on experience, culture and age. In addition to, predictor variables are added to the predictive algorithms. The learning interface should focus on both cognitive and affective states of the responsive agents. The author in [8] discussed about predicting the student performance on failure of a student. They have found that student failure and dropout are the major problem. A simple data mining technique was studied for predicting the dropouts. They have achieved better performance using decision tree systems. The author in [9] discussed about the prediction of instructor performance via data mining techniques. They developed a tool for analyzing, understanding and resolving the educational and administrative problems. Questionnaire method is used for analyzing the instructor's performance. Classification algorithms are used for teachers and student perception. The author in [10] depicted performance of the student evaluation where the amount of stored educational data is of high. They have studied about artificial neural networks and discriminant analysis models which improved accuracy and specificity. They evaluated on student responses databases and then applied classifier models. It has been observed that understanding level of students mainly depends on interest towards the course. The author in [11] studied to find out the dropouts using student database systems. They have examined a model for utilizing grouping to enhance understudies' learning knowledge that would result in a change in the nature of the instructive condition of organization. The classification algorithms have degraded the accuracy of the classification results. The author in [12] discussed about the data mining technology for instructors' performances via multiple channel such as joint recruitment enrollment, athletic enrollment and application enrollment. The algorithms were evaluated in computer science program of Nigerian university. It was found that mathematics subjects have highest rate of students performed using C4.5 algorithms.

The author in [13] studied about the combination of decision tree and regression analysis. In the decision tree algorithm, CART and CHAID algorithms were used for predicting the teacher performances. The results have proven that teacher who performed satisfactory results based on course validation.

Summative values which influence teachers' self-reported and self-directed activities is measured from survey [1][RA-4].

In [14], the algorithms like ID3, CART and C4.5 were used to predict the student results which help to validate the teacher performances. Their prediction models were relied on psychological, personal, social and other environmental variables. The result has proven that better results of teaching quality. The author in [15] studied about the distributed data mining for predicting the brightest career and the teaching quality. It has been evidently seen that amount of information increases when the database contains secret information. In order to make an effective decision-making process, local and global knowledge is updated. It stated that the generalized information makes use of a classifier for making global decision systems.

3. Research Methodology

This section presents the proposed technique of the higher education systems using an intelligent agent system. The aim of the study is to predict and suggest the teaching attributes for instructor's performance in higher education systems using an intelligent agent.

3.1 Data collection and Profile Modeling

In order to discover an effective knowledge, the collection of records should be efficient. Turkiye student evaluation dataset which composes of 5820 instances with 33 attributes is used. With reference to previous study [16,17], the selected attributes are [RB-1] [RA-1] Q3, Q5, Q9, Q10, Q11, Q13, Q14, Q15, Q16, Q18, Q19, Q23, Q24, and Q26. The main feature of any dynamic systems is to symbolize the features of an effective teaching quality. This profile model creation combines the learning style of the students in order to predict the instructor's performance. Initially, the learning style of the students is gathered. Thus, a knowledge level attributes are collected in four categories, namely, apprentice, beginner, intermediate and expert. In a similar way, the educational contents of a domain are formalized via elementary units namely, teaching objects. These teaching objects are then promoted for sharing and reusing those dynamic contents with the assistance from elementary units. The Table 1 represents the teaching attributes and its teaching objects.

Table 1. Learning Attributes and Learning Objects

Learning's attributes	Learning objects	
Knowledge level	Teaching Types	Teaching Levels
	Graphic	Easy
Apprentice		
Beginner	Video	Intermediate
Intermediate	Text	Advanced
Expert	XML	Expert

It has been generally observed that each elementary unit's exhibits varying levels of learning style.

3.2 Ants as Intelligent Agents

This works addresses the decision-making process in the educational field that describes the performance of the teacher using the student's profile. It has been modulated for teachers to identify their strength and weakness of the teaching quality. Here, we have used filtering agent and learning path agent based on obtaining teaching style of the teachers.

3.3 Filtering Agent

Filtering agent assists the students to look for appropriate content of a course. In addition to this agent, the dynamic course generator agent, is used for recommending the upcoming students to select the appropriate learning path. It helps to optimize the learner's course based on profile's similarities.

3.4 Teaching Path Agent

Most of the educational site modeled in the graph where nodes are teaching objects and edges are teaching activities. Thus, the training path of a particular profile is different from another path of another profile with varying interests. Based on teaching attributes, the teaching styles are recommended from the student's profile. The teaching quality can be predicted via ants as an intelligent agent.

The process is as follows:

a) A novel Teaching Objects (TO) is inserted or updated. The antecedent route is automatically erased when the novel Teaching Route (TR) is inserted. The issue arises is the fitness towards the learner's ability, i.e how to impress the learners. When any updating in the learning route, the learner objects should well-utilized. The antecedent TO is erased. If any route is eliminated, the association with that route is also removed. The accumulated data is lost. When the lost data has more information about the teaching objects, then it may encounter a serious issue. Thus, the crammer should aware before removing TO. Merging of TOs may possible. Some associations in the TO must be re-estimated. In order to recommend best instructors, the interaction process, fitness evaluation and decision-making process should be processed effectively.

Ant's Teaching Style is as follows:

Steps	Description
1.Solution Construction	The number of populations in finite space of agents A and its solution A= {a_1, a_2…a_n}.
2.Heuristic Information	In this process, the neighborhood information is collected. The best and worst bound of all agents are estimated. In the minimization problem, $best(t) = \min fit_n(t)\ n \in \{1,....i\}$ $\text{worst}(t) = \max fit_n(t)$ Where $fit_n(t)$ represents the fitness value of n at iteration t.
3.Agent's Updating	There is a possibility of arriving new agents in the system. The agent should place, according to its suitability of the system. By estimating the agent's position, the new agent is located accurately.
4.Local search	In order to locate the new agent, the prior information about the old agents is examined. Based on the local information, agents are processed at different iteration level t.

3.5 Heuristic Information Process

In this process, we describe the teaching style of the instructors between objects 1, objects 2 and objects 3. The teaching route modeled in Figure.1.

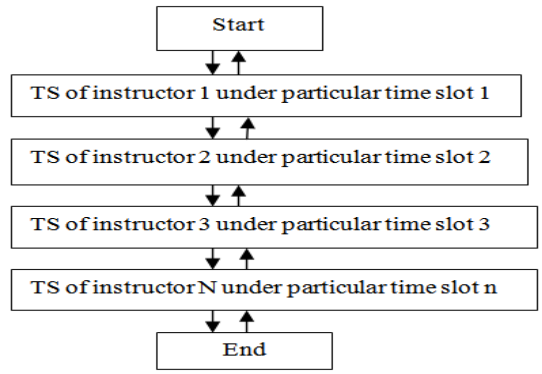

Figure 1. Route Formation for Teaching Style

Based on the knowledge level of instructors, the teaching style differs and thus, the creation and existence of knowledge occur. Though, the contents are satisfied by the learners, the main teaching attributes such as beneficial for professional development, knowledge updating, well-planned, commitments, good speech delivery and positive approach to students are to be focused. In accord to time, content delivery is significant attributes for predicting and recommending the teaching style. Let ants be the agent that describes the dynamic teaching objects. It is arbitrarily selected based on criteria. When the instructor models the resource item f, then the knowledge node of {f} via transition arcs linking. At each trial, the current state of the instructor is reassigned at the knowledge edge. This process is called as 'heuristic' update of the trails in knowledge subspaces. For the given instructor x, the local update of pheromone of teaching objects in subspace S is given by,

$$\tau = (1 - \delta)\tau + \delta\Delta\tau \quad (1)$$
$$\Delta\tau = \mu_s(x) * \tau_0 \quad (2)$$

Where, τ is the current pheromone of an arc (teaching objects),
δ is an evaporation parameter,
$\Delta\tau$ is the updating in pheromone level under the membership degree μ_s

It is generally observed that the visited path is marked, so as to predict the potential paths. In similar cases, when the trails of the knowledge subspaces are altered during competency level via feedback or self-assessment or self-evaluation systems. And also, depends on membership levels of corresponding knowledge subspaces. It is known as a global update of the knowledge spaces is given as:

$$\tau_{path} = (1-\rho)\tau_{path} + \Delta\tau_{path} \quad (3)$$

Where

τ_{path} is the set of pheromone values of edges in the path.

ρ is evaporation parameter.

$\Delta\tau_{path}$ is the change of pheromone values on edges of path.

More the no. of agent visits, the teaching style network is formed. Searching of good styles prefers searching of good paths, even the pheromone evaporates.

3.6 Local Search Strategy

In each step, the decision should be made for assigned ants to select the events or node next to visit. It is also generally perceived that 'new ants' attracts and follows the path of previous ants (instructors). Even, if the solution is not optimal, based on the time taken by new ants determines the quality and thus become part of the main styles. Concurrently, the newly discovered ants should fit with the teaching styles. If an ant A chooses a teaching objects in its local solution at time t is given as follows:

$$P_i^A(t) = \{\frac{[\tau_{i(t)}]^{\alpha}.[\varphi_i]^{\beta}}{\sum_{u\varepsilon J^m}[\tau_{u(t)}]^{\alpha}.[\varphi_u]^{\beta}} if i\varepsilon c^A \quad (4)$$

Where,

c^A is the set of solution added to the teaching objects of ant A.

$\alpha \geq 0$, $\beta \geq 0$ are two parameters that determine the importance of pheromone value and its heuristic desirability.

3.7 Agents Updating Strategy

In some cases, the agents may be bidirectional ie. It visits any teaching objects at particular iteration. The global updating of the agents forms from predecessor and the successor path of an ant. If teaching objects (TO), the position of new agent is determined as

$$NewAgent_{pos_i}^{A}(t+1) = newagent_{pos_i}^{A} * \mathrm{Trate}_i^d(t+1) \quad (5)$$

Where, Trate is the teaching rate.

The teaching rate is defined as the teaching styles between two instructors. It is estimated from its antecedent path. The teaching is estimated as:

$$Trate_i^d(t+1) = rand_i Trate_i^d(t) + P_i^A(t) \quad (6)$$

Where rand is the random number ranges [0, 1].

Above equation determines how efficiently the infrequently used paths are deleted. In the point of new or edited material, a heuristic search is performed over the newly created TO. This investigation arrangement may cause an issue when the nature of good ways is in great circumstances. In that condition, it ought to be smarter to take after existing edges of the best ways. Then again, when the nature of the best ways is poor, investigation of unvisited edges ought to be urged to discover better learning ways. To accomplish this objective, we receive a versatile arbitrariness control arrangement so the haphazardness control parameter is associated with the nature of the best-discovered way, which is assessed by the assessment criticism on the difference in student competency.

4. Results and Discussion

This section presents the experimental analysis of the proposed method. We predict the performance of the instructors using ACO algorithm. A new teaching object is inserted and the performances are evaluated. The records are collected from Turkiye student evaluation dataset that composes of 5820 instances with 33 attributes. This paper is an enhancement of the previous paper is stated in Table 2 thus, the pre-process step and the feature selection steps are already performing.

Table 2. Features selected

Sl.No	Features selected
Q3	Amount credited is worth
Q5	Updated and efficient Resources
Q9	Beneficial for professional development
Q10	Changed my lifestyle
Q11	Updated knowledge
Q13	Well planned for taking classes
Q14	Committed toward courses
Q15	Arrive on time for classes
Q16	Good delivery of speech
Q18	Eager to help the students
Q19	Positive approach to students

Q23	Responded to questions
Q24	Better evaluation to measure course objectives
Q26	Treated all students equally

Table 3 Parameter Settings

Parameters	Value
No. of agents (a)	50
Max. no. of iterations (t)	100
No. of instructors (C)	3
No. of attributes (d)	14

Then, Search Direction Sea_D = (Sea_{D1}, Sea_{D2} ……. Sea_{Dk}) and the heuristic search action Sea_A = (Sea_{A1}, Sea_{A2}… Sea_{A3}). In Table4 the search direction determines the centroid of the LO at the ith agent with dimension d. The dimension d denotes the dimensionality of the test data records. Initially, the Sea_Dset to 1 and sequentially updates during the search progression. Toward the finish of the ebb and flow cycle, another centroid is produced utilizing the momentum centroid, ebb and flow look course and ebb and flow seek step. Some change is perceptible in the first and second highlights, though the third and fourth highlights stay unaltered. Therefore, at the next iteration, for both features 1 and 2, the search process continues on the current direction. For the 3rd feature, the current search direction is 0, which means in the previous iterations no improvement happened to this feature in both directions**.** Thus, for the following emphasis, the hunt step is partitioned by 2 and the pursuit bearing is set to 1. In the respect of the last component, the inquiry heading is set to - 1 with a specific end goal to scan for a superior arrangement the other way since there is no opportunity to get better in the present course**.**

Table 4. Heuristic Information about Agents in the Teaching Routes

	Q5	Q11	Q13	Q19
Centroid $_{\text{Pres}}$	4.53	1.24	7.56	0.32
Sea_D	1	-1	0	1
Sea_A	0.2	0.3	0.1	0.09
Centroid $_{\text{nvalue}}$	4.82	1.19	7.36	0.44
Centroid $_{\text{fvalue}}$	4.82	1.19	7.36	0.36

In the education management scenario, the heterogeneity of the data in various learning management systems describes a lot of issues in data sharing and prediction. The issues like impeccable data integration, retrieving accurate result for user queries and discovering the informed search are under heterogeneous teaching systems. Though, several e-learning architectures are introduced, the selection and recommendation of the best web service are not widely explored. Teaching efficacy was based on the foundation of self-efficacy. The social learning theory and made it a definite of the conviction that one can successfully execute the behavior required to produce the outcomes. This concept more narrowly defined teacher confidence is less influenced by emotional factors outside the realm of teaching than teacher self-efficacy. Ant colony optimization algorithms has applied for the combinatorial optimization of instructor evaluation, which is dynamic problems in nature due to the real variables, stochastic problems, multi-targets and parallel implementations due to the subject taught and level of students understanding. ACO produce near-optimal solutions for Predicting Instructors Performance in Higher Education Systems Using ACO Systems, the results will be changing dynamically; the Ant Colony algorithm can be run continuously and adapt to changes in real time [RA-2].

5. Conclusion

Ant colony optimization algorithm is a delicate processing technique that demonstrates a handles vulnerability and deficiency of an issue and builds the way that has most extreme adjustment. This investigation proposes a calculation in view of the insect settlement improvement strategy and the possibility of idea guide to consequently build the appropriate instructing way that can adjust to the students. In this paper, we suggest a novel ant colony optimization model which assists both students and instructors [RA-3]. The framework executes in two steps, i) to place the teaching objects in its appropriate and accurate position using Ant as an intelligent agent. ii) Suggesting the knowledge for predicting the instructor's performance in a collaborative environment. Experimental analysis has been carried out in Turkiye Student Dataset in which 14 attributes are selected. Since the aim of the study is to predict and suggest the teaching style of the instructors using student feedback data. Information filtering agent is used to find the appropriate teaching objects for giving instructors. With the help of filtered information, a certain set of teaching styles was predicted from the initialized teaching objects. From the results, the significant attributes are Q5, Q11, Q13 and Q19 play a vital role in suggesting and predicting the instructor's performance. On comparison with existing models, Inherent parallelism of ACO performs better than other Optimization algorithms such as particle swarm optimization (PSO), cuckoo search optimization (CSO) for predicting instructor performance. Positive Feedback of ACO leads for rapid discovery of good prediction with more accuracy. ACO provides crisps results and PSO is applicable for problems, which are in fuzzy nature[RA-3].

References

[1]Cory Koedel, Jiaxi Li, G.Matthew, and Li Tan, "Teacher Performance Ratings and Professional Improvement", Journal of Research on Educational Effectiveness, Vol. 12:1, pp. 90-115, DOI: 10.1080/19345747.2018.1490471, 2019[RA-4].

[2]S. Tan , E. Lau, and H. Ting, "How Do Students Evaluate Instructors Performance Implication of Teaching Abilities, Physical Attractiveness and Psychological Factors", Soc Indic Res, Vol. 146, pp.61–76 ,2019[RA-4].

[3]J.A. Larusson, and B. White, "Learning Analytics: Moving from concept to practice. New York: Springer Science Business Media", 2014.

[4]R. Bourbia, H. Seridi, and A. Seridi, "SAAD: An adaptive e-learning platform using IMS Learning Design", IEEE Multidisciplinary Engineering Education Magazine, Vol 3, No 4, 2008.

[5]E. Popescu, "A Course Authoring Tool for WELSA Adaptive Educational System", ICCC 2008, pp. 531-534, 2008.

[6]T. Wang, "Using a style-based ant colony system for adaptive learning", Expert Systems with Applications 34, pp. 2449–2464, 2008.

[7]Canales, "Adaptive and intelligent web based education system: Towards an integral architecture and framework", Expert Systems with Applications, 33, pp. 1076–1089, 2007.

[8]N. Stash, "Incorporating Cognitive/Learning Styles in a General-Purpose Adaptive Hypermedia System", PhD Thesis, Eindhoven University of Technology, Netherlands. 2007.

[9]Y.M. Huang, J.N. Chen, T.C. Huang, Y.L. Jeng, and Y.H. Kuo, "Standardized course generation process using dynamic fuzzy petri nets", Expert Systems with Applications, 34(1), 2007.

[10]D. Milosevic, "Designing lesson content in adaptive learning environments", International Journal of Emerging Technologies in Learning, 1, 2 , 2006.

[11]J. Chen, "Applying dynamic fuzzy Petri net to web learning system-Interactive Learning", 13(3), pp.159–178, 2005.

[12]H. Chorfi, and M. Jemni, "PERSO: Towards an adaptive e-learning system", Journal of Interactive Learning Research, 15, pp. 433–447, 2004.

[13]P. Paredes , and P. Rodriguez, "A Mixed Approach to Modeling Learning Styles in Adaptive Educational Hypermedia", Advanced Technology for Learning, 1 (4), pp. 210– 215, 2004.

[14] Rao, A. N., Vijayapriya, P., Kowsalya, M., & Rajest, S. S. (2020). Computer Tools for Energy Systems. In International Conference on Communication, Computing and Electronics Systems (pp. 475-484). Springer, Singapore.

[15]R. M. Felder, and L. K. Silverman, "Learning and teaching styles in engineering education", Engineering Education, 78(7) , 674–681, 1988.

[16]N. D. Flemming, "Modes of Presentation (V.A.R.K.) in the Tertiary Classroom", Research and development in higher education. Proceedings of the annual conference of the higher education and research development society of Australia (HERDSA), Vol. 18, pp. 308–313, 1995.

[17]D. A. Kolb, "Learning style inventory technical", Boston McBer &Co. 1974.