Assessing Learning Behaviors Using Gaussian Hybrid Fuzzy Clustering (GHFC) in Special Education Classrooms

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Abstract

The article suggests an unsupervised model for featuring student's learning patterns in an open-ended learning scenario. The article proceeds by generating powerful metrics to characterize the learner's behavior and efficacy through Coherence investigation. Then, the selected features are combined through a Gaussian Hybrid Fuzzy Clustering (GHFC) that categorizes students based on their learning patterns. The proposed system features the essential behaviors of every group and associate the behaviors with ability to develop right models to gauge the learning gains between pre- and post-test scores. Also, this article explains the deployment of behavior characterization to be developed as a adaptive framework of learning behaviors.

Keywords: Affective State Transition, Unsupervised Learning, Cognitive State Transition, Likelihood Metric, Fuzzy Clustering.

1 Introduction

Learning starts from the first day of our lives by learning essential activities and eventually evolving to learn complex activities. Learn generally occurs through transfer of knowledge fro man instructor whose role is shared by parents, siblings, or teacher in school (Cantor, P., et al, 2018). As time evolves, humans are expected to learn on their own without any guidance so that they apply their knowledge to solve real world problems. Many automations have been developed to assist the learning in the absence of a teacher. The automations or the computer system take the place of an instructor and supports students in learning. Though these systems can render knowledge to students, they do not interact with the student. This is a hindrance on the learning session.

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Open-Ended Learning Environments (OELEs) offer the learners with authentic but meaningful learning by involving the students in problem-solving that is a combination of testing, developing and revisiting their own solutions (Land, S. 2000). Nevertheless, the novice learners tend to face challenges in conceiving, developing and further application of the knowledge into strategies succeed (Winslow, L.E. 1996). This raises a demand for scaffolding and feedback mechanisms to improve the proficiencies (Kinnebrew, J., et al., 2017).

The proposed research focus around the development of CTSiM, an OELE to foster the learning of computational thinking (CT) and science concepts by deploying learning by modeling strategy. In this environment, the students develop their own simulation models through agent-based and block-structured visual language. This is fastened with the help of supporting tools to test and verify their so developed models (Winslow, L.E. 1996 & Sengupta, P., et al. 2013). The Pre- and post-tests in previous studies revealed that the CTSiM have exhibited enhanced learning gains in both the domains namely CT and science. Nevertheless, a multitude of challenges are confronted by middle school students in conceiving, developing and further applying their acquired knowledge and modeling skills when they try to develop science models in CTSiM environment (Sengupta, P., et al. 2013). Students use different strategies to assist learning and model developing activities. But still selecting suboptimal strategies retard the learning and further aggravate the difficulties in model building. To aid the learning community to combat the challenges, an adaptive feedback mechanism which is to be integrated on automated detection, evaluation, and identification of learning patterns (Basu, S., et al., 2017 & Segedy, J.R., 2015).

Most of the legacy systems are designed with an intend to help in learning by providing the cognitive as well as affective feedback to the learners in problem solving or exploration of the environments (Arroyo, I., et al., & Baker, R.S., et al., 2007). Tracking both the cognitive as well as affective states have facilitated these systems to completely model students apart from imparting better understanding.

These facts were harnessed for the design and identification of appropriate feedback mechanism for learners. D'Mello and Graesser (D'Mello, S., et al., 2014) suggested a comprehensive model that considered cognitive as well as affective elements to demonstrate the transformation of emotions during the learning process. Augmenting to this, the model also anticipates learner's behavior and issue suitable feedback when the student's experience emotions that hinder their learning. The learners employ computer-based environments to learn as well as to get involved in non-learning tasks. Some of the cognitive states and affective states are isolated to direct the off-task activities like gaming and conversation with fellow students (Baker, R.S., et al., 2007). Though the environments hinder the students from involving in non-learning tasks, the students adopt self-learning. Even though they cannot manage their complete learning process, still they thrive to learn less by spending more time (Baker, R.S., et al., 2007). This article proposes a complete exploratory Machine Learning (ML) model to isolate the student's behaviors in a case study approach to demonstrate the efficacy of the proposed approach.

2 Proposed Methodology

Students' modeling and learning processes in CTSiM environment is seen as a coagulation of five vital activities: (1) perceiving and securing domain information and other CT-related ideas from hypertext resources (2) construction of an abstract but conceptual model in science domain through an agent-based framework; (3) developing computational models that mimics behavior of the agent through a block-structured language with visual effects; (4) model execution to analyze the behaviors as generated by Net Logo (Wilensky, U) and (5) verification of the model's correctness by comparing the behaviors as emanated by an expert model which could execute synchronously. The complete model building activity and its behavior comparison with its interfaces are showed in Fig. 1. Elaborate details of the presented CTSiM environment is employed in middle school science and was very successful (Winslow, L.E. 1996 & Sengupta, P., et al. 2013).

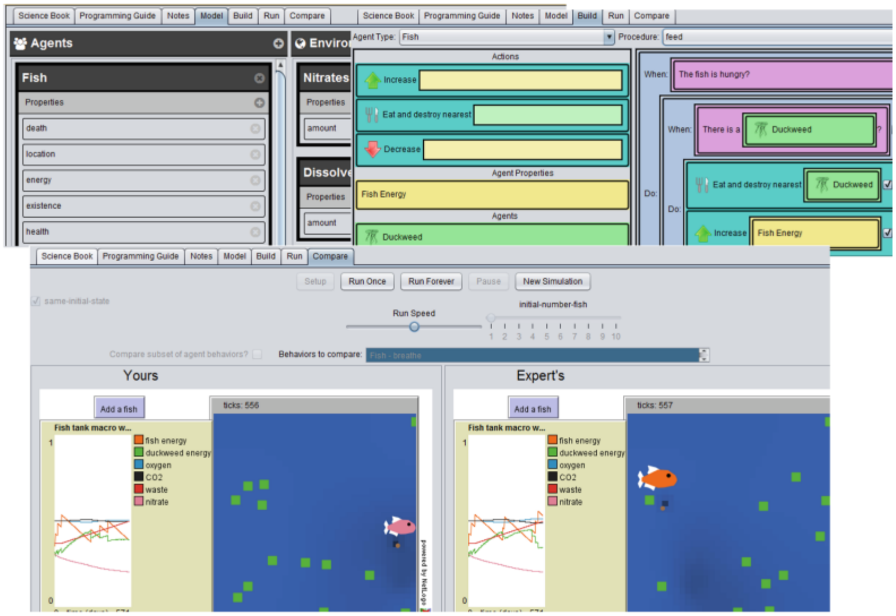

Figure 1: Conceptual, Behavior, and Computational Interfaces of CTSiM

The legacy research in CTSiM, have demonstrated good learning improvement with 2 introductory training tasks whereas with 3 modeling tasks. The learners familiarize with the interfaces and functionality of the system by creating agents to draw shapes as well as spirals, which is a direct kinematics learning. The three learning activities comprises of modeling the tasks under 2 topics pertaining to science: (1) advanced kinematics which is represented as unit. Here the learners model a rollercoaster car that moves on a track, and (2) ecology-based task. Here the learners initially create a macroscopic and microscopic model of a fish tank, which is perceived as unit 4 and 5 respectively. The macroscopic model concentrates on implementing fish and aquatic plant's behavior along with their food chain. But this model is not stable. So, in unit 5 the learners add microscopic elements like bacteria and implement waste cycle to create a more sustainable fish ecosystem model. The preceding studies have revealed that the learners enthusiastically learn science as well as other CT concepts CTSiM (Winslow, L.E. 1996 & Sengupta, P., et al. 2013).

Building Model

The model building process CTSiM comprises of various problem-solving strategies and learning pedagogy. Hence, they can demonstrate a wide range of learning behaviors in students. The proposed work attempts to collect features from behavioral characteristics, so as to create an adaptive scaffolding as a primary means to grouping of learning behaviors. To perform this task, the methodology describes the behavioral nature of the learners wholly dependent on multitude of metrics associated with a specific task model. This work also assesses the quality of the developed model in CTSiM environment. Appropriate feature selection method is applied on the feature space, to attain optimal metrics which are closely relevant to clustering the students based on their behavior. The Gaussian hybrid fuzzy clustering (GHFC) is solely used to form the clusters.

Development of Suitable Measures that can Describe the Learning Behaviors

In the preceding works, a more popular Coherence Analysis (CA) is deployed to create a model-based analytical framework, that inherently analyze the problem solving and learning patterns (Basu, S., et al., 2017 & Kinnebrew, J., et al., 2017). The CA along with other performance metrics cumulatively characterize the feature space to elaborate the learning behaviors. The theory-based framework inclines to follow top-down approach that is responsible to identify the leaners action in any OELE which can be further categorized into one of three types: (1) acquisition of information (IA), (2) Construction of solution and (3) assessment of the so developed solution (SA) (Basu, S., et al., 2017). Each of these tasks can be further drilled down into hierarchical subtasks, where the leaves indicate the individual actions performed by the learners CTSiM. The IA tasks includes activities like searching, identification and understanding of all the essential information to build and correct models in the appropriate resource libraries. SC mainly concentrates on development as well as refinement of both computational and conceptual models. The action carried out in SC may be an edit operation on the models like augmenting a trait to the agent or eliminating a feature from it. SA activities comprise of executing the simulations in the learner developed model. It also compares the model's behaviors with an expert model as explained in Section 2. Students are allowed to undergo the activities in the order they prefer. Tracking the combinations in which they order the tasks and the manner of switching among the tasks is very vital to learn about the learners and problem-solving capabilities (Basu, S., et al., 2017).

The performance measure for assessing any action is done as a unary relation termed as effectiveness. This could effectively capture whether the performed action leads to appropriate solution. For instance, including an appropriate component or weeding off an inappropriate component from the model may characterize more effective strategy or action. Looking forward individual actions, the proposed CA delineates a support among any two actions namely $x \; and \; y, x \rightarrow y$. This implicitly means that the action y follows the action x, only if y consumes the information produced by the prior action x then it means that x supports action y, and vice versa. The CTSiM's CA is applied to a set of some 22 measures that can feature the student's deployment of learning strategies. Apart from this, the unary and binary metrics that are already defined, a third measures, termed as proportionality, which could effectively characterize the ratio of specific genre of actions. For instance, the term compare percentage elucidates the ratio of learners model against the cumulative count of actions.

Selecting Appropriate Features and Generating Clusters Using Gaussian Hybrid Fuzzy Clustering (GHFC)

Among the 22 CA measures that are taken for consideration, it has likelihood that few examples have comparatively lighter variance. These measures are nor effective in providing sufficient information to distinguish learners based on their behaviors. Hence feature selection method are applied to select the more appropriate measures that can positively contribute for cluster formation.

The proposed FCM clusters the features by organizing and aggregating the pixels that belong to the same class. To start with, the pixels of the image are organized as a fuzzy matrix, to make the process simpler. FCM clustering in not capable of regularizing the inherent noise in the image. Also, it is not highly successful when scaled to higher dimensions. To cope up these, the images are clustered through Sparse FCM. The sparse FCM can effectively regulate the clustering model by the introduction of model parameters to make the model more suitable for hierarchical clustering. The Sparse FCM that is reformulated is given as,

$$\underset{\varphi(\mathrm{V})}{\max} = \sum_{\mathrm{x}=1}^{\mathrm{p}} \mathrm{u}_{\mathrm{x}} \left(\mathrm{K}_{\mathrm{x}}, \varphi(\mathrm{V})\right) \; (1)$$

The term$\varphi(V)$ is the regularization parameter. Also, sparse FCM delineates the clustering framework as

$$\max_{r,\varphi(V)} = \sum_{x=1}^{p} \mathrm{r_x} u_x \,(K_x, \varphi(V))\ (2)$$

Here $\mathrm{r_x}$is the pixel value that is dependent on objective function. The representation of sparse FCM is give as

$$\max_{\mathrm{v,k,r}} \mathrm{F(K,k,r)} = \mathrm{r^T BCSS(V)}\ (3)$$

The BCSS(V) is weights among cluster summation of squares. Also, sparse FCM clusters by using the centroid (C_{S_FCM}).

The proposed GHFC, the cluster centroids take the responsibility to be identified by both the schemes that are altered by constant α. This represents a Gaussian function. The primary purpose of the Gaussian function is to regulate or normalize the continuous events, that are binomial. The Gaussian distribution function is also used for determining the centroid which eventually increases the likelihood of obtaining improved clusters. The equation for determining the optimal centroid is presented below:

$$C = \alpha C_{FCM} + \beta C_{S\_FCM}\ (4)$$

The terms C_{FCM} and C_{S_FCM}represents the centroids that are eventually identified by the sche, esFCM and Sparse FCM respectively. The constant β is actually derived from α, i.e., $\beta = 1 - \alpha$. The Gaussian function α is mentioned as,

$$\alpha = \frac{\sum_{x=1}^{p} \frac{1}{2\pi\sigma^2} e^{-\frac{(u_x - \mu)}{2\sigma^2}}}{N} \qquad (5)$$

The term μ represents the mean of the image whereas σ is the variance of the image. P is the count of pixels in the image segment. Deploying the Gaussian function to find the aggregate centroid, certainly improves the segmentation accuracy. Apart from this, it is also used for hybridization of the results from FCM as well as Sparse FCM to make the model more robust in handling noise.

The significant features of the clusters are used to feature the learning pattern pertaining to the clusters. The analysis on the data sourced from a classroom of 98 middle school students in Nashville, TN.

3 Experimental Results

The experimentation is conducted in 6th-grade classroom which comprises of students in the age group of 11–13-year-olds. They were observed for 3 weeks in science classes. On day 1, the participants were asked to attend pre-tests in paper-pen mode on three topics namely kinematics, ecology, and CT. On Day 2, all the learners were asked to attend a lecture on agent-based modeling in the CTSiM environment. On third day, the students studied Unit 1 whereas on fourth day they were asked to work individually on drawing spirals. Students were then subjected to work individually even on Unit 3 and to build a rollercoaster model on subsequent days. On seventh day the learners were actively participated in the post-test on kinematics post-test as well as on CT. The next five days, the students were made to work as individuals to build the fish tank ecosystem, which is to be perceived as a macroscopic model. Then the microscopic model is added on the system. At last, all the learners were made to attend the ecology post-test as well as second post-test on CT.

The process of clusters generation is deployed through Gaussian hybrid fuzzy clustering (GHFC) on a subset of metrics handcrafted by feature selection. The cluster size was maintained as 6. Euclidean metric is used to find the distance. For about 1000 random restarts were done to control the impact cluster center selection. Table 1 summarizes the average as well as Standard Deviations (SD) of the clusters.

Table 1: Mean Cluster Values Pertaining to Rollercoaster Modeling Activity (*.p is Maintained as Less than 0.05)

Metrics	**CT learners at n value as 2**	**Aimless comparators at n value as 24**	**Efficient learners at n value as 2**	**Non-strategic tester sat n value as18**	**Tinkerers at n value as36**	**Unsystematic builder sat n value as16**
CT read	1474* (506)	11.1(24)	106 (139)	28 (45)	56 (110)	34 (59)
Conc. edt %	7.8 (4.8)	39*(1.9)	10.1 (6.3)	6.3 (3.1)	5.0* (2.1)	11.7* (7.5)
Comp. edt %	22.0 (1.2)	21.8* (4.9)	45.5(14)	28.9 (5.1)	35.3 (5.3)	47.4* (6.6)
Concep. Size	7.0 (2.4)	7.7 (3.9)	10.5 (0.8)	5.3* (2.7)	8.1 (4.2)	6.4 (3.2)
Comp. size	5.4 (0.8)	4.4* (0.8)	5.0 (1.4)	3.9* (0.6)	6.0* (1.1)	6.7* (2.1)
Test %	49* (10.7)	32.1 (4.5)	16.5* (4.8)	44.4* (6.0)	34.7 (4.3)	29.7* (5.5)
Compare %	18.1 (15)	37.8* (6.3)	6.8 (1.4)	16.8* (4.9)	21.4 (5.0)	8.7* (3.4)
Compare part	12.8 (19.5)	34.6* (5.2)	58.3* (11.8)	20.4* (12.9)	31.9* (8.2)	15.6* (13.9)
SC to IA %	0.9.9 (0.6)	0.5* (0.4)	3.5* (3.7)	1.1 (1.3)	0.6 (0.8)	0.7 (0.7)
SC to SA %	15.3 (6.5)	21.1* (4.4)	11.7 (3.8)	21.3* (3.8)	14.1* (2.6)	12.4* (4.3)
SA to IA %	0.7 (0.3)	0.4 (0.4)	8.7* (1.4)	0.8 (0.5)	0.7 (1.0)	0.8 (1.3)
SA to SC %	5.8 (2.3)	6.1* (1.6)	25* (2.7)	12.2 (3.7)	9.8* (2.4)	18.4* (5.5)

Table 2 displays the following measures: learning gains starting from the pre- till the assessment of post-tests both in the domain as well as in CT, model distance among the models developed by students and expert model. The distances that are closer to 0 indicates that the modelling is better.

Table 2: SD and Average of Performance by Clustering in RC

Cluster	**Domain gain**	**CT gain**	**Conc. dist**	**Comp. dist.**
Efficient learners whose n value is 2	12.00 (8.49)	4.00 (1.41)	10.50 (0.71)	11.00 (0)
Tinkerers whose n value is 36	3.99 (5.00)	2.14 (2.14)	7.20 (1.89)	12.5 (11.1)
Non-strat. testers whose n value is 18	6.50 (6.40)	0.64 (2.05)	8.39 (1.54)	14.00 (8.93)
Unsys. builders whose n value is 16	4.59 (6.22)	1.09 (1.27)	9.40 (1.96)	12.45 (5.15)
A. comparators whose n value is 24	4.11 (3.70)	0.76 (2.46)	8.08 (1.77)	16.83 (11.28)
CT learners whose n value is 2	−2.85 (0.40)	2.00 (0)	7.00 (0)	19.50 (3.54)
All students whose n value is 98	4.49 (5.39)	1.11 (2.12)	8.49 (1.84)	14.09 (9.84)

4 Conclusion

This article presents in integrated research on learner behaviors as well as its performance as exhibited by the performance clusters in two genres namely pre-post learning gains and building models. The detailed experimentation on the cluster's learning features imparts multiple but valuable insights that can be leveraged to formulate adaptive scaffolds for every formed cluster. The derivation of CA metrics and clustering are combined as the recent version of CTSiM to characterize the 6 behaviors as indicated by the clusters reported. The article also presents generic methods to (1) formulate actions in any OELE, (2) quantize the relation between learner's actions through CA and (3) select the appropriate metrics that to feature the learning patterns. Detailed analysis of learning behaviors gave in depth insights on distinctive learning behaviors and also on the deployment of learning strategies. Augmenting to this, the study emphasized that learners with better understanding outperformed the ad hoc learners. Also, the study infers that a vast majority of learners improved their learning autonomously.

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