Apply Concept Density Algorithm to Personalized Game-based Learning

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Abstract: In this paper, we propose a concept density algorithm for personalized game-based learning. The use of density algorithm allows the system to compute the concept density automatically for the given content. Based on the analysis, the system provides the tutoring information and auto-generated questions to self-assess on personalized learning. The personalized learning flow generated by the density algorithm fits perfectly to the gaming flow. Moreover, the proposed algorithm achieves the adaptive learning from the concept level of learning.

Keywords: Game-based Learning, Concept density, self assessment, adaptive learning

Introduction

Computer games are fun and engaging. Since students cannot move their eyes away from the computer games, the teachers tend to add educational material into game and turn it into an advantage of motivating students to learn. Personalized learning experience can be reinforced by adding game elements to the environment. Personalized game-based learning has gained a lot of focus from researchers and developed various applications in recent years [1-3]. Some essential elements in games have been examined to explain their engaging nature. A "fun" game should include goals, interaction, immersion, reward system and more [3]. It satisfies the players' intrinsic and extrinsic motivation [4]. Taking these characteristics into learning, the elements of fun, interactivity, problem solving, user involvement, and creativity in game can be used to transit the pedagogical information to players while playing.

This paper focuses on the issues of personalized game-based learning and proposes a concept density algorithm to compute the concept density automatically for the given content. Based on the analysis, the system provides the tutoring information and auto-generated questions to self-assess on personalized learning.

1. Personalized Game-based Learning

1.1 Issues in Personalized Game-based Learning

Although game-based learning opens up great varieties of leaning, issues and controversy exists between game and learning. The most controversial issue is that the more educational elements the game has and the less fun the game is. How to get balanced between game and education is widely discussed [3]. In personalized learning, without the presence of teacher, how to evaluate the learning status and provide tutoring information also need to be addressed. Studies to find the key factors of a "fun" educational game point out the basic game-based learning framework [5][6].

1) Learning
   Educational game has to be custom designed integrating with cognitive development and learning behaviors. Huitt and Hummel declare the different cognitive developments for different age levels of learners which need to be taken into consideration for the game design [7]. Slavin defines different types of learning behaviors and based on these promotes learning motivation and outcome [8].
2) Game elements
   According to Alessi and Trollip [9], the content is an integral part of the game structure. With the interactive effects such as multimedia, story scene, and user interfaces in game, the learning content has to immerse into game design. In addition, feedback such as rewards in game is also a key element for game designer to motivate students to learn or driving students to the desired learning activities [3].

1.2 Concept-based learning

Bruner, Goodnow, and Austin [10] promoted a learning style called "concept learning" or "category learning". They defined concept learning as "the search for and listing of attributes that can be used to distinguish exemplars from non exemplars of various categories." Therefore, concept learning is a learning strategy that students learn knowledge based on the concept level. Students will through this training be able to recognize the learning object containing concept-relevant features and use them to classify the objects into groups or categories.

Concept abstraction level determines the effectiveness of the concept learning. Concepts contain different degrees of information ranging in simplicity and complexity. When a concept is more difficult, it will be less likely that the learner will be able to recognize and learn the concept. In the other hand, for the simpler concept, the learner is easier to spot and construct to a more complex concept based on the association rules.

2. Concept Density Algorithm

To accomplish concept-based learning, the system itself needs to have the capability of recognizing the abstraction hierarchy of the concepts. Extracting concepts from the content has been well achieved through keyword extraction, ontology, or other text mining techniques. However, recognizing a single learning object containing how much concept information and the abstraction level is still a challenge. We propose a concept density algorithm that allows the system to extract the concepts from the learning objects, and in the mean time, compute the concept density for each learning object.

Table 1. Learning content formation

	A1	A2	A3	A4	A5
S1	A1'1	A2'1	A3'2	A4'1	A5'3
S2	A1'3	A2'1	A3'1	A4'3	A5'1
S3	A1'2	A2'1	A3'3	A4'2	A5'3
S4	A1'1	A2'2	A3'2	A4'2	A5'1
S5	A1'3	A2'2	A3'1	A4'1	A5'1

For a given learning content, it can commonly be formatted as Table 1 where S_i represents the learning object and A_i represents the pre-defined attribute for each learning object. Once the format is done, the concept analysis can be applied. First, the number of possible concepts is retrieved by the equation 1. Based on the result, Table 1 now can convert to the aspect of concepts shown in Table 2. Clearly, the count of each concept appears in the learning content can be computed. This information also can use as the threshold to cut off the non-significant concept.

CAC = (1)

$$[(C_1^{m1} + 1) * (C_1^{m2} + 1) * (C_1^{m3} + 1) * (C_1^{m4} + 1) * \dots \dots] - 1$$

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23
A1	A1'1	A1'3				A1'1	A1'1	A1'1	A1'3	A1'3	A1'3				A1'1	A1'1	A1'1	A1'3	A1'3	A1'3		A1'1	A1'3
A2			A2'1			A2'1			A2'1			A2'1	A2'1		A2'1	A2'1		A2'1	A2'1		A2'1	A2'1	A2'1
A3				A3'1			A3'1			A3'1		A3'1		A3'1	A3'1		A3'1	A3'1		A3'1	A3'1	A3'1	A3'1
A4																							
A5					A5'3			A5'3			A5'3		A5'3	A5'3		A5'3	A5'3		A5'3	A5'3	A5'3	A5'3	A5'3
count	2	2	3	2	2	1	0	1	1	2	0	1	2	0	0	1	0	1	0	0	0	0	0

Table 2. Learning content concept view

To define the concept density, we consider both frequency and the concept weights. Equation 2 shows the definition of initial concept density (ICD) where *CDvalue* represents the weight of each concept and *count* represents the frequency of each concept appearing in the learning content. Table 3 demotrates the output of the initial concept density A1 with the unified weighting, 100. To put it simply, the initial density table indicates that concept *C13* has the highest concept density which weights the most and appears most frequently. Therefore, *C13* is considerly the first candidate of the learning concepts for the given content. Initial Concept Density (ICD):

ICD (i,j) = (2)

$$(\sum_{k=1}^{j} CDvalue(C_i, A_k)) * count(C_i)$$

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23
TCD-1	200	200	300	200	200	200	0	200	200	400	0	200	400	0	0	300	0	300	0	0	0	0	0

Table 3. Initial Concept Density

Other than the concept weights can be evaluated by the proposed algorithm, the concept density table changes its values indicating the learners' learning status. Once the target concept is assessed and passed, the concept weight will be set lower gradually using the equation 3 where *ZAcount* represents the number of concepts with zero weight. The weight change of the target concept will affect other concepts containing partial attribute values same with the target concept. To synchronize the changes, equation 4 updates the weights of the concepts which relate to the target concept. *COWCA* in equation 4 represents the updated attribute value due to the change of equation 3.

CDMW(i,j) = (3)

$$(\sum_{k=1}^{j} CDvalue(C_i, A_k) - (ZAcount(C_i) * 20)) * count(C_i)$$

CDOW(i,j) = (4)

$$\left(\sum_{k=1}^{j} COWCA(i,k)\right) * count(C_i)$$

3. Personalized Game-based Learning with Concept Density Algorithm

To apply the concept density algorithm to personalized game-based learning, the system model is shown in Figure 1. Here we use the monopoly model as the game-based framework which is commonly used in game-based learning. Other gaming types such as RPG, adventure game or puzzle game for game-based learning can be also adapted to this model. Modules other than gaming modules are the game-based learning modules which include learning record, content and exam modules. The content module manages the learning contents. Through this module, the teacher can focus on editing and updating the leaning content without considering the presentation in the game. The exam module provides the assessment of the learning content. The learning record module records the learning status of the players throughout the game including time, achievement, leaning goals, learned concepts, etc.

The system model shows that the concept density algorithm module is applied to analyze the learning content and generate the questions automatically to feed the exam module. After the teacher input the learning content, the concept density algorithm will analyze the content and extract the concepts. The teacher then can select the proper concepts from the result. Based on the selected concept, the concept density algorithm then can compute the highest-scored concept and use the corresponding objects to generate the assessment question.

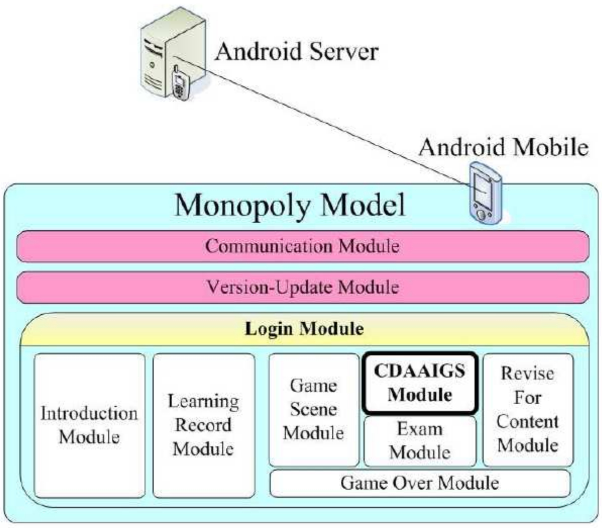

Figure 1. System model

Figure 2 shows the learning flow with the concept density algorithm. In step 1, teacher inputs the learning content based on the individual need. The system will convert the material into required format and analyze the concepts in step 2. Step 3, the system computes the concept density table and uses that to select the concept for personalized learning. For the next step, the system generates the question automatically based on the selected concept from the previous step. From step 5 to step 8, system goes to the learning loop. The system will update the concept density table according to students' answer and learning status.

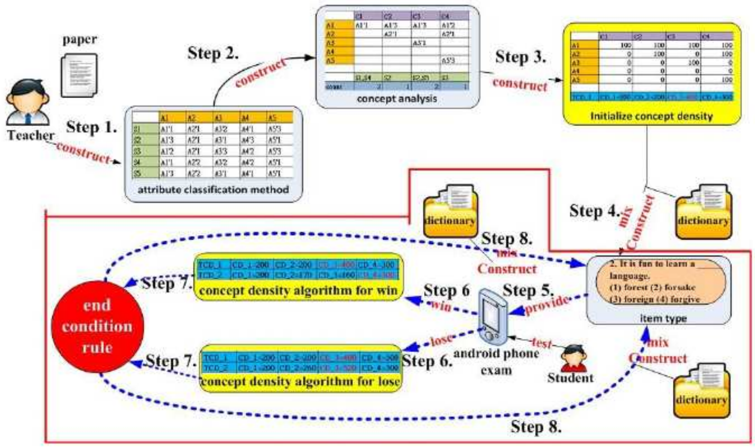

Figure 2. Learning Flow with Concept Density Algorithm

4. Experiment

We implement a personalized English learning game based on the proposed model and algorithm. The game is developed under mobile android environment for the future mobile game studying. The game elements include reward system, competition, and problem solving. Figure 3 shows the demo interfaces of the game. Figure 3.a is the login interface for the student status record. Figure 3.b shows the main interface of the game. Figure 3.c demos the problem solving interface. The reward system also embeds to the problem solving interface by providing tools to help players to solve the problem.

There exist four units of English learning material. Teacher selects around 10 out of extracted concepts from each unit. System sets up the scoring criteria using concept density. A preliminary survey is carried out to validate the system effectiveness. A further experiment will be followed to provide more evidence. The questionnaire is based on the TAM model. Furthermore, it also surveys the attitudes toward internet usage, mobile device using, and mobile game-based learning. The results show positive feedback on the mobile game-based leaning. However, the effectiveness of learning needs further study.

(a) (b) (c)

Figure 3. Game-based learning with concept density algorithm demos

5. Conclusion

Several advantages of applying concept density algorithm to personalized game-based learning. First, the concept density algorithm can ease the teachers' loading by generating the questions automatically based on the selected concepts. The learning content thus can be personalized upon the request. Second, the concept abstraction level reveals naturally according to the concept density computation. Third, the learning flow generated by the density algorithm fits perfectly to the gaming flow. The scoring and rewarding system in game can match to the concept density tightly. Last but not the least, the concept density weights change according to the players' interaction. Each student will experience different learning flow based on the learning status. That makes the adaptive personalized learning in this model practical. In the future, the system can extend the application to self-tutoring and remedy learning since the system records the learning status from the concept level.

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