An Adaptive Tool for Learning

Jer Lang Hong

Abstract Various approaches have been made to make students adaptively learn through online learning. With the advancement of Internet technologies and the wide application of e-learning tools, it is certainly possible to provide effective learning tools for younger generation of learners. The younger generation of learners are more Internet savvy, and they tend to learn through online material which provides easy-to-use menus and functionality. However, few online tools provide adaptive learning materials to these generations of learners, and most of them are rather static in nature and provide simplistic functions. In fact, studies have shown that different learners have different learning abilities, and thus, they require a different set of learning materials. In this paper, we proposed a novel adaptive learning tool which could effectively gauge the user's learning behavior and adapt the content material to suit his needs. Our preliminary study shows that the users show positive response to our tool.

Keywords Web 2.0 · E-learning · Adaptive behavior

1 Introduction

The introduction of Web 2.0 has enabled Web browsing and navigation easier. From the traditional static Web to dynamic server-based Web, users can now generate their own content by posting their opinions through various sources such as blogs and forums (Figs. 1, 2, and 3). With the advancement of Internet technologies, Web users are able to experience a more personalized Web browsing and cater for their usage and needs. Recently, researchers incorporate learning tools

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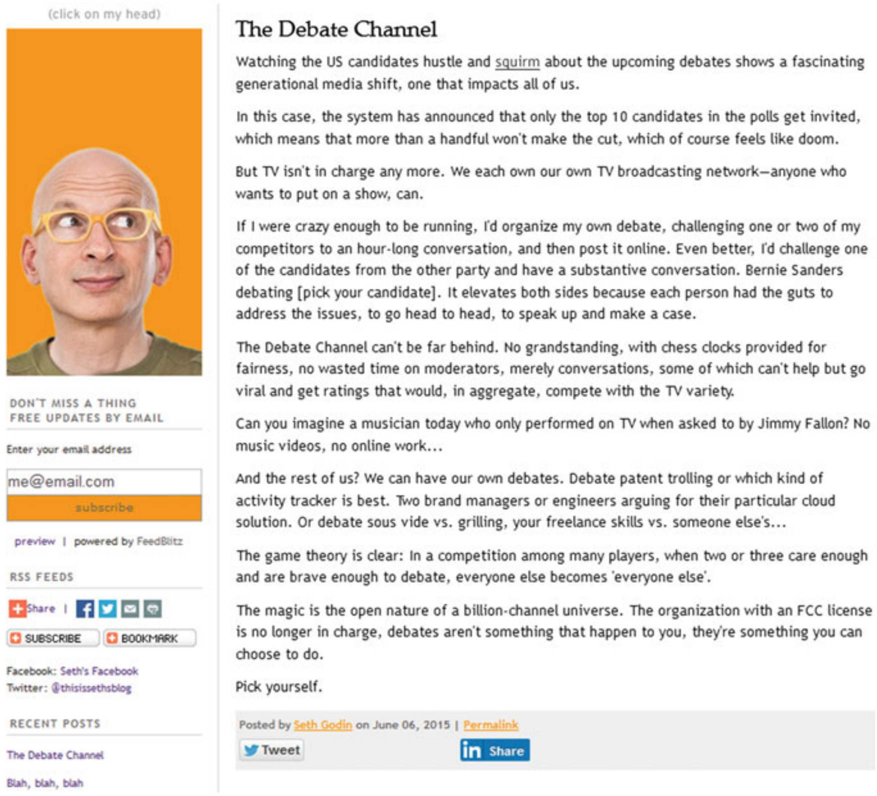


Fig. 1 Blog site

using the dynamic features of Web browsing. For example, in the recent Graduate Record Examination (GRE), an online adaptive examination is presented whereby the examination difficulty level is set according to the user answer (Fig. 4). Though different users answered different sets of questions according to their ability and they obtained different scores at the end of the examination, GRE has managed to show that the generation of questions using a set of predefined rules is able to differentiate the users' skills accurately. Inspired by the adaptive nature of GRE examination online tools, we proposed a novel adaptive tool for e-learning whereby users are able to learn through dynamically generated contents by browsing the Web. Statistics have shown that there is an increase in adoption of e-learning tools. In fact, research has shown that e-learning is proven to improve individual learning skills, especially the younger generation.

The paper is divided into several sections. The next section describes research related to ours, while the subsequent section explains the methodology in detail. Then, we present our experimental results, and finally, we conclude our work.

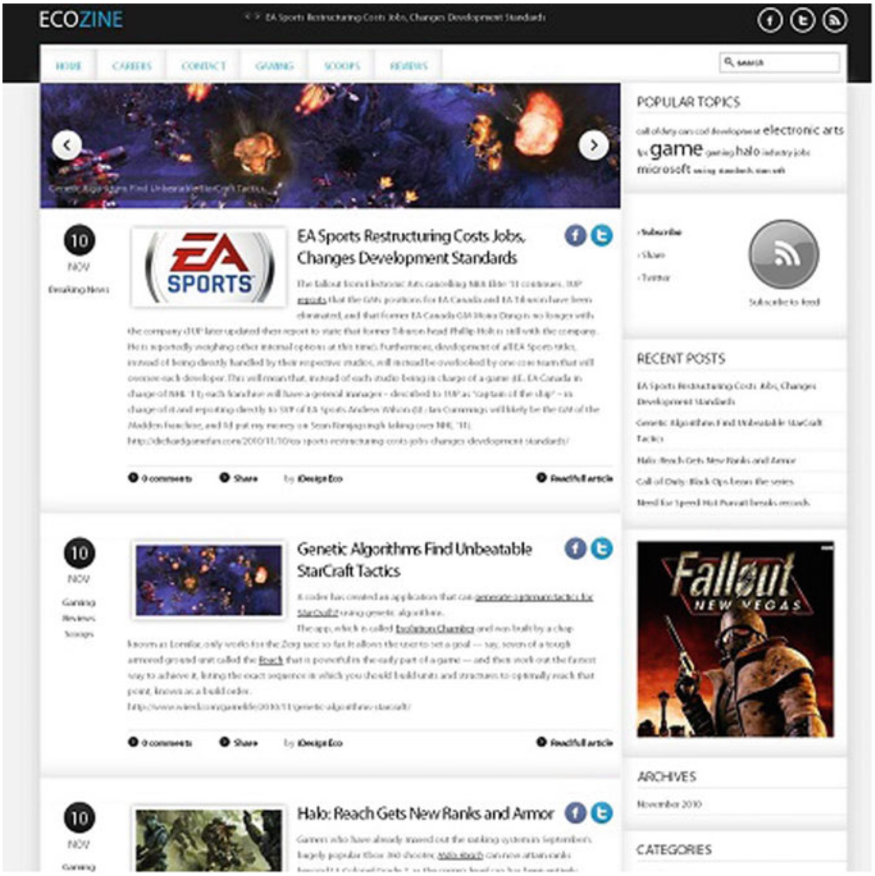


Fig. 2 WordPress example

2 Related Work

Snow develops an adaptive e-learning tool by combining perspective of differential psychologist, experimental psychologist, personality psychologist, and cognitive scientist. Recently, work has been developed in examining the ATI issue using computer as the environment (Maki and Maki 2002; Sternberg 1999). Shute proposed a model where different users with different learning skills learn through an e-learning environment (Shute 1993). Examples of relevant characteristics include incoming knowledge and skills, cognitive abilities, personality traits, learning styles, and interests. To maximize the system performance, one should leverage these different skills and make full use of it. This includes observing the degree of learning and the extent where it can further be developed.

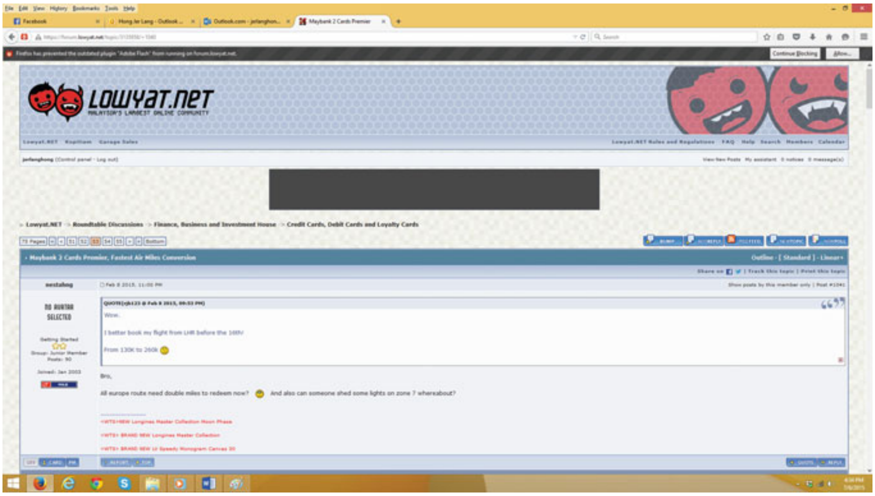


Fig. 3 Lowyat forum

Fig. 4 GRE sample questions

103. Concerning the transcription of a *lac* operon, the synthesis of mRNA starts from which part of the operon?
A. From the beginning of the promoter
B. From the middle of the promoter
C. From the beginning of the operator
D. From the middle of the operator
E. From the beginning of the *lac* Z gene

104. Self-splicing, which does not rely on protein-based enzymatic activities, is found in the splicing of:
A. Double-stranded RNAs.
B. mRNA precursors.
C. tRNA precursors.
D. rRNA precursors.
E. snRNAs.

Furthermore, individuals differ in how much they learn and what they learn, and the different outcomes of their learning reflect the differences in learning processes. The implications mapping the different skill sets of users have been discussed in the literature of (Ackerman 1996, 2003). Recent advances in cognitive science, psychometrics, and technology have make it possible to assess higher-level learning skills (Hambleton 1996; Mislevy et al. 1999) compared to earlier traditional methods such as paper-and-pencil multiple-choice tests, new assessments for complex cognitive skills involve embedding assessments directly within interactive, problem-solving, or open-ended tasks (e.g., Bennett and Persky 2002; Mislevy et al. 2001).

3 Proposed Methodology

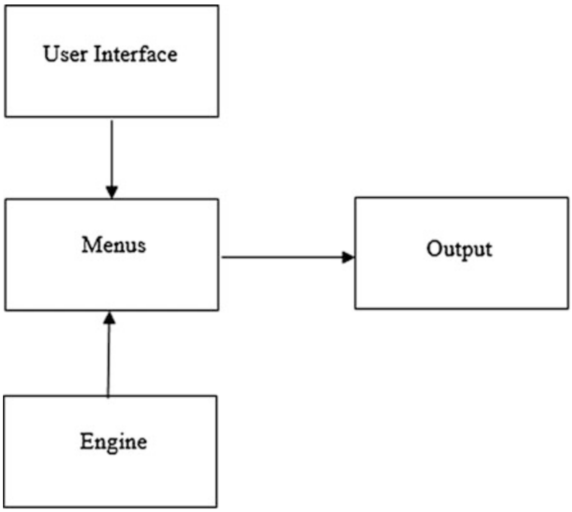
3.1 Overview

Basically, our system comes with an intuitive yet user-friendly interface (Fig. 5). The interface provides easy-to-navigate menus as well as dynamically generated contents. The system is equipped with backend engine which is able to process the user's request, learn, and adapt to the user's needs. The system also has local storage which is able to store every user's activity and keep a log of it. The idea behind the adaptive learning system is threefold. First, we are of the opinion that different users have different interest and learning curve. Therefore, providing a highly dynamic learning material suits the user's needs more. Secondly, the users are able to grasp the learning material and learn progressively should the materials presented dynamically. Finally, adapting the learning materials promotes more user engagement, and it helps to understand the user's needs better.

3.2 Interface

For the interface part, the user will go through easy-to-navigate menus to select his preference of learning materials. Once the user has selected his preference, a

Fig. 5 Architecture of our system



start-up menu will be given where an overview and tutorial on how to use and navigate the system are provided. Then, the learning material is provided to the user in animated forms. The user can then navigate through the learning materials by simple browsing.

3.3 Adaptive Engine

Our system incorporates a backend engine which could dynamically adapt to the user's browsing behavior. Leveraging on the common user's behavior such as clicking, scrolling, and typing behaviors, our engine is able to deduce the typical user interaction, hence deducing the interest of the users. Inspired by machine learning and its ability to deduce user's activity, we incorporate Markov chain and genetic algorithm to learn the user's activity and adjust the browsing experience accordingly.

A thorough investigation and careful examination show that user's activity is a complex problem, and hence, a proper machine learning is required. A graph of user's activity is constructed, and a careful analysis is deduced. Our observation shows that the higher number of clicks generally indicates higher interest among users, though in some cases this may not be necessarily true. A scrolling behavior normally indicates better interest among users.

3.4 Output

The system outputs a log file and stores the activity of users in XML form. Users' activities are important for future usage as well as further analysis. When the user logs in to the system again in the future, his personal data and activity are loaded from the log file and personalization will be carried out where necessary.

4 Experiments

We conduct experiments to gauge the effectiveness of our system. We randomly select 20 different users from wide range of background and skills to test our system. The demographic of our users is as.

As is shown by the Tables 1 and 2, we choose random sample of users from diverse background. Preference was taken to select users who are IT savvy and in the age group of 20–25. Users are given instructions on how to use the system as well as briefed on the setup. They are given a grace period of 2 h to use the system and give feedback on it. A survey form is given to them to fill up the necessary details.

Table 1 Users' age group

Age range	Number
15–20	3
20–25	10
25–30	3
30–35	2
>35	2

Table 2 Skill set of users

Skills	Number
Engineering	3
Computing	10
Business	5
Others	2

Table 3 User-friendliness test

Rating	Number
Poor	0
Not satisfactory	2
Neutral	3
Satisfactory	12
Excellent	3

Table 4 Performance

Rating	Number
Poor	0
Not satisfactory	3
Neutral	3
Satisfactory	10
Excellent	4

Table 5 Learning experience

Rating	Number
Poor	0
Not satisfactory	1
Neutral	5
Satisfactory	9
Excellent	5

On the whole, users find our system to be user-friendly, and our system comes with an interactive GUI, together with easy-to-navigate menus (Table 3). Some of the users commented on the color and font size of the system, whereby a more appropriate color scheme can be used with an adjustable font size. The system is able to run effectively without any crash incident reported, and neither bug is detected (Table 4). Table 5 shows the learning experience of the users. As shown in the table, users generally learn new knowledge through the easy-to-navigate menus as well as the interactive interface. A few comments have been given by the users over the fixed navigation provided (e.g., the sequence of menus seems to be rather constant after navigating).

5 Conclusion

We present a novel adaptive learning tool whereby the system is able to dynamically adapt to different sets of user activity and response. The system is equipped with personalization tool where the user behavior is captured and various relevant responses are given based on the users' need. Experimental test shows that our system is responsive to the users' need and is able to adapt well across wide range of user's responses.

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