A Learners' Personalization Preference Analysis Model Applied to E-Learning Content Recommendation in Consideration of Time Effect

Gwo-Haur Hwang[a*], Beyin Chen[b] & Sherry Y. Chen[c]
[a]*Department of Information Network and System Administration, Ling Tung University, Taiwan*
[b]*Department of Information Management, Ling Tung University, Taiwan*
[c]*Graduate Institute of Network Learning Technology, National Central University, Taiwan*
*ghhwang@mail.ltu.edu.tw

Abstract: The accelerative update of the knowledge makes lifelong learning become important. But learners' preference may change over time. Therefore, in this paper, a personalization preference analysis model for e-learning content recommendation is proposed. The model is modified from e-commerce and is based on the half-life theory. It is expected that the model can also be applied to e-books' recommendation.

Keywords: E-learning content recommendation, half-life theory, personalization preference

1. Research motivation

Human beings are at the era of the dramatic increase in knowledge and information. Thus, scientific and technological knowledge is doubling from the nineteenth century every fifty years, the mid-twentieth century every ten years, and to the end of the twentieth century is every three to five years (Lai & Lin, 2004) [4]. The accelerative update of the knowledge makes lifelong learning become important. For lifelong learning, e-learning may be a popular learning style in the future. However, so many of the e-learning resources make the learners hard to look for their needs. The analysis on user preference in e-commerce is very popular (Chen & Wu, 2002; Ting, You, & Hsiao, 2002; Lai & Hwang, 2010) [2, 5, 7]. In the e-learning, most of the analysis is applied to the adaptive learning with learning styles (Hwang, Sung, Hung, Huang, & Tsai, 2012; Nedungadi & Raman, 2012) [3, 6]. As mentioned in the paper by Zhang, Zhang, and Xu (2012), for individual lifelong learning, the popularity of e-learning resources may change over time [8]. Similarly, learners' preferences may also change over time, but such research topic on e-learning is less mentioned.

Lai and Hwang (2010) proposed a selection and recommendation system for web advertising delivery, which included a very detailed derivation model for the consumers' preference associated with the advertising products in consideration of the time effect [5]. In this study, part of the derivation process is adopted and modified to apply to a personalization preference model associated with e-learning content. It is expected that the model can be applied to e-learning content recommendation in e-learning area.

2. The learning content preference analysis model

In this study, the main variable of the model of learners' preference is the record of the learners' behavior on the learning web site (including the times of clicks and the times of learning content download). The derivation of the model includes two steps as follows:

Step 1: Establish the equation of the preference level. A learner's preference is accumulated by two factors: the times of clicks and the times of learning content download. Learning content download is the more important factor of the two factors. Therefore, the following equation using a learning content download weight to enhance the preference level of the learning content download is presented.

$$P = DW + C$$

In the above equation: P is the level of a learner's preference; W is the download weight; D is the times of download; and C is the times of clicks. The download weight W is defined as follows.

$$W = (TotalC + 1) / (TotalD + 1)$$

In the above equation, TotalC is the total times of clicks of the learning content, and TotalD is the total times of learning content download. So, W is the average times of clicks per download. The reason of plus 1 is to avoid the denominator to be zero, thus resulting in the value of W becoming infinite. When increasing in the value of TotalC and TotalD, the effect of plus 1 decreases.

*Step 2: Establish the equation of the time-varying preference.*As mentioned earlier, the impact of the time effect to preference should be taken into account. In this study, the half-life theory is used to derive the time-varying value of the preference.

(1) Half-life theory

The meaning of half-life is that the strength of radioactive material will decay into half of the origin after some period of time. There exists half decay time for each radioactive material. Finally, the radioactive material does not disappear, but in the attenuation of a period of time, its radioactivity becomes very small (Lai & Hwang, 2010; Chang, 1991) [1, 5]. In accordance with the half-life theory, it is assumed that the learners' preference of a particular kind of learning content decays into a half after d_0 days, where d_0 is dependent on the nature and the preferred degree of the learning content. In other words, if the initial preference is P_0, then the preference after d_0 days will fell to $P_0/2$. The equation can be written as follows.

$$P_{d0} = P_0 / 2$$

(2) The preference after d days: P_d

After d days, the half-life value of the preference is defined as P_d and expressed as the following equation: $P_d = P_0 / (2^{d/d0})$

By defining a daily attenuation coefficient $\alpha = 1 / (2^{1/d0})$, the equation can be written as: $P_d = P_0 * \alpha^d$

(3) The cumulative preference until today: CumP

It is known that the preference will be attenuated because of the time effect, and then the preference accumulated until today can be defined as CumP and expressed as the following equation:

$$CumP = P_0 + P_1\alpha + P_2\alpha^2 + ... + P_n\alpha^n$$

Where P_0 represents the preference level obtained from the behavior record of today; P_1 represents the preference level of yesterday; P_n represents the preference level of n days before today. However, each calculation must begin to run from the first browse, which is very time-consuming. Therefore, the above equation can be modified as follows:

$$CumP = P_0 + \alpha (P_1 + P_2\alpha + P_3\alpha^2 + ... + P_n\alpha^{n-1}) = P_0 + \alpha CumP_y$$

This means that the accumulated preference until today is the preference of today adding the accumulated preference until yesterday multiplied by the attenuation coefficient α.

3. Conclusions

The accelerative update of the knowledge causes that learners may change their learning preferences over time quickly. The learners' learning content preference analysis in consideration of time effect can calculate learners' recent interests. According to that, it can filter out the excessive amount of learning resources and make appropriate recommendation to learners when they select learning content. The model, which is based on the half-life theory, proposed in this paper is providing a reference when implementing such a recommendation system for e-learning content.
The model proposed in this paper is only a preliminary result. The variable can be analyzed further in order to model more accurate. For example, the times of the download can be subdivided into two factors, which are the times of the download and the amount of the download. The reason is that the downloaded file size should also affect the preference level and must be considered probably.

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