Smart Jump: Automated Navigation Suggestion for Videos in MOOCs

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ABSTRACT

Statistics show that, on average, each user of Massive Open Online Courses (MOOCs) uses “jump-back” to navigate a course video for 2.6 times. In this work, employing one of the largest Chinese MOOCs, XuetangX.com, as the source for our research, we study the extent to which we can develop a methodology to understand the user intention and help the user alleviate this problem by suggesting the best position for a jump-back. We demonstrate that it is possible to accurately predict 90% of users’ jump-back intentions in the real online system. Moreover, our study reveals several interesting patterns, e.g., students in non-science courses tend to jump back from the first half of the course video, and students in science courses tend to replay for longer time.

Keywords

MOOCs; user intention; video navigation

1. INTRODUCTION

How to design “smart” interactions to improve student engagement is one of the major challenges of MOOCs since the low completion rate of the courses [3, 4]. Recently, a few researches have been conducted on the click-level interactions between users and the MOOC systems in order to better understand how users learn and what they need when watching video [1, 2]. We found that the jump-back is a frequent behavior with strong user intention. On average, each user of Massive Open Online Courses (MOOCs) uses “jump-back” to navigate a course video for 2.6 times. In this work, we study the extent to which we can develop a methodology to understand the user intention and help the user alleviate this problem by suggesting the best position for a jump-back. To precisely illustrate the problem we are going to deal with, we give an example scenario in Figure 1.

2. DATASET AND OBSERVATION

Our study is based on the data from XuetangX, one of the largest MOOC platform in China. The dataset used in this study includes six courses from XuetangX which can be categorized into two types: science (Computer Science, Electronic Engineering and Economics) vs. non-science (Language, Art and Culture) courses.

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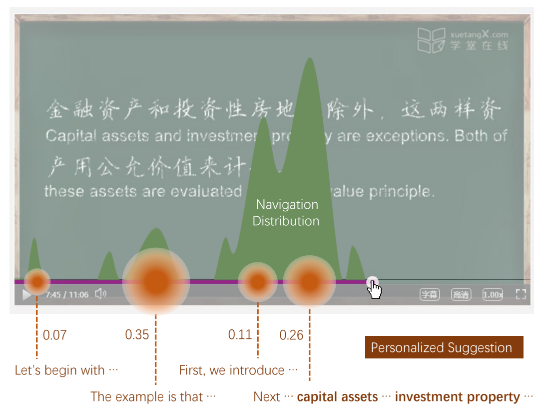

Figure 1: Personalized jump-back suggestion for a specific user. The distribution of possible end positions for a jump-back is shown above the navigation bar. The red circles with different size represents possible end positions, where a larger circle means a larger probability. We also show the context transcripts around each red circle to illustrate the content.

Here we give the definition of an important concept **Complete-jump**.

Definition 1. ***Complete-jump.*** *A complete-jump consists of one (or multiple) jump-back actions by the same user on the same lecture video, aiming to find the right position to rewind. We use the tuple (u, v, p_s, p_e) to denote a complete-jump that user u jumps back from start position p_s to end position p_e in video v.*

Please note that in the definition, the complete-jump may consist of multiple jump-back actions, which means that the user may jump back to a position of no interest and continue to seek for the position that she wants to replay. This also implies that in a complete-jump behavior, there might be a jump-forward action. For example, the user jumps back far away and then wants to jump forward a bit to correct it.

After reconstructing complete-jumps, we engage in some high-level investigation of the factors that cause users to jump to different positions in a video from two perspectives:

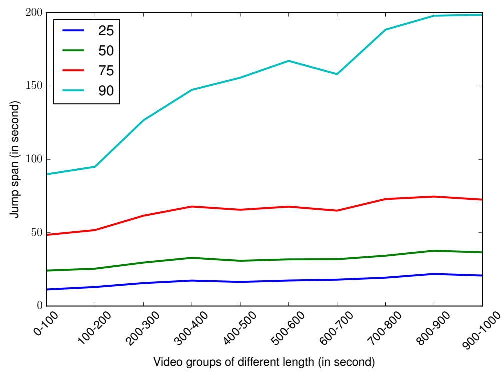

Figure 2: The distribution of different percentiles for jump span in different video length groups. Y-axis: position of jump span percentiles. X-axis: video groups of different length.

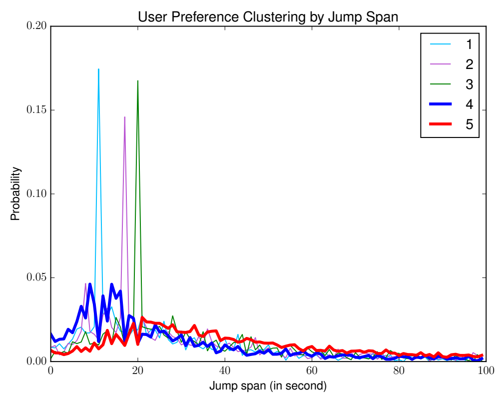

Figure 3: Cluster users into five categories by their complete-jump records. Y-axis: the probability of different jump spans. X-axis: jump span (in second). Category 1, 2, 3 represent users that have obvious preference, while category 4 and 5 represent users that almost have no preference.

general performance and user preferences. The investigation about the differences of general performances has two levels of granularity: (1) By course. After calculating the average start position and the span of complete-jumps, we found that users in non-science courses tend to rewind to the first half of a video, while users in science courses tend to minimize the rewind and only jump back from previous part of the video. (2) By video. Figure 2 shows the correlation between video length and jump span. In the investigation of user preferences, we categorize users into different types based on their jump span records leveraging k-means clustering. Figure 3 shows the result of user clustering.

3. METHOD

Based on the observations above, we extract a number of features which are adapted into a predicting model, i.e., Factorization Machine (FM). For each tuple (u, v, p_s, p_e), we define a set of features and construct a data instance $\mathbf{x}_i$, and compute the suggestion score by:

Table 1: Ranking performance of our method based on FM model and baseline method based on frequency with the measurement of hits@n

Course	Method	n = 1	n = 2	n = 3	n = 5
Science	Baseline	33.21	53.21	66.15	81.99
	FM	**37.05**	**60.40**	**76.04**	**89.59**
Non-science	Baseline	39.26	62.61	76.64	91.30
	FM	**42.25**	**72.42**	**88.43**	**96.05**

$$\hat{y}(\mathbf{x}_i) = w_0 + \sum_{j=1}^{d} w_j x_{i,j} + \sum_{j=1}^{d-1} \sum_{j'=j+1}^{d} x_{i,j} x_{i,j'} \langle \mathbf{p}_j, \mathbf{p}_{j'} \rangle \quad (1)$$

where $y(\mathbf{x}_i) \in [0, 1]$ indicates the likelihood of user u jumps to the corresponding position of $\mathbf{x}_i$; $\mathbf{p}_j, \mathbf{p}_{j'}$ are two k-dimensional latent vectors and $\langle \mathbf{p}_j, \mathbf{p}_{j'} \rangle$ models the interactions between variables $x_{i,j}, x_{i,j'}$ with the dot product of two latent vectors.

4. RESULTS AND DISCUSSION

We use the predicting result of FM to compare our automatic suggestion method based on machine learning model with the baseline method based on frequency through a ranking experiment. We use hits@n to measure the suggestion of the true end positions of all complete-jumps. Table 1 shows the result of the ranking experiment. We can see that our method based on machine learning model clearly outperforms the method based on frequency both in science courses and non-science courses.

In summary, we studied an interesting problem of automated navigation suggestions in MOOCs. We use a large collection of data from the courses of Xuetangx.com, providing investigating on jump-back behaviors from different perspectives. We found several interesting patterns and revealed the main factors that influence users' navigation behavior. Based on the discoveries, we developed a methodology aiming to understand the user intention and to suggest the best positions for a jump-back. Our experiments validate the effectiveness of the proposed method. We are also applying the method to a real online system and expect to have the function online very soon.

5. REFERENCES

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