Profiling MOOCs from viewing perspective
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Abstract

We profiled three aspects of MOOCs from the perspective of viewing behaviors, the most prominent and common ones of MOOC learning. They were learner classification, course attraction, teaching order and learning order. Based on viewing behavior data, we provided a non-parametric algorithm to categorize learners, which helped to narrow the scope of finding potential all-rounders, and a method to measure the correlations between teaching order and learning order, which helped to assign teaching contents. Using information entropy, we provided an index to measure course attraction, which integrated the viewing time invested on courses and the number of viewed course videos. This index describes the diminishing marginal utility of repeated viewing and the increasing information of viewing new videos. It has potential to be an auxiliary method of assessing course achievements.

Introduction

Massive open online courses (MOOCs) have emerged from the integration of education and the Internet [1]. They break the boundaries of time and space, expanding traditional education due to their transmission of information by the Internet technology. And they have been viewed as an accelerator for learning and a solution to educational resource imbalance [2,3]. Differences between traditional courses and MOOCs lie in several dimensions, involving conditions of admission (pretesting vs. no-condition), student motivations (homogeneous vs. heterogeneous), classroom management (supervised vs. unsupervised), interactions (face-to-face vs. online), dropout rates (low vs. high) [4,5]. Moreover, MOOCs are featured as learner-centered, which is different from the knowledge-centered feature of traditional
education. Therefore, understanding MOOC learning behaviors helps to assess MOOC achievements, to find methods of improving MOOC quality, and so on.

Analyzing MOOC learning behaviors has become a hot topic in the MOOC community, which includes learning motivations, learning achievements, and so on [6–9]. MOOC learners are motivated not just to pass exams which involve understanding particular concepts, or some parts of course contents [10–13]. Their diversified expectations and motivations to learn MOOCs result in high course dropout rates and low exam participation rates [14–18]. Viewing behaviors are the most prominent and common in MOOC learning, compared with other behaviors such as doing exercises, discussing and testing. Therefore, profiling MOOCs from viewing perspective can involve as many learners as possible.

We profiled MOOCs from viewing perspective in following three aspects. Firstly, we provided a method to categorize learners into two types, which helped to narrow the search range of potential all-rounders. Secondly, we provided an index to measure course attraction based on course learners’ the number of viewed videos (calculated in a continuous way) and their relative viewing time length compared with video length. Thirdly, we provided a method to measure the correlations between teaching order and learning order based on learners’ viewing order and video labels, which helped to optimize teaching content assignment.

MOOC learners’ behavior data cannot inherently pose answers to assess courses because the causal relationship between learning more and learning better is unclear [33]. So our results might not be the exact MOOC contributions to learners. However, the low values of those indexes can help us to find some imperfect aspects of some MOOCs. Note that the order correlation cannot be applied to humanities courses, but can to natural science courses.

This paper is organized as follows. The data are described in Section 2. The indexes such as entropy are described in Section 3. The indexes of attractions and those of the correlations between teaching order and learning order are described in Sections 4 and 5. The conclusion is drawn in Section 6.

Viewing behavior data

MOOC platform iCourse (http://www.icourse163.org) provided the viewing behavior data of eight courses (01/01/2017–10/11/2017). The courses were selected from natural sciences, social sciences, humanities and engineering technology. Each course had substantial registrants so that our results were statistically
meaningful. The data included time length of each video. For each learner, the data included the viewing start time and the viewing time length of each video he viewed.

Since some selected courses were not finished before 10/11/2017, our discussions focused on the measurements of course attractions on the level of videos, and on the measurements of correlations between teaching order and viewing order, to which the data of some weeks were adequate. Videos could only be downloaded by iCourse app. If the app disconnected to the Internet, the information of viewing downloaded videos cannot be collected. Accordingly, our discussions only involved online viewing behaviors of MOOCs.

### Table 1. Specific statistical indexes of the data provided by ICourse.

| Course       | Course Id       | a   | b   | c       | d       | e       | f   |
|--------------|-----------------|-----|-----|---------|---------|---------|-----|
| Calculus     | 1002301004      | 2.955 | 129 | 8.081   | 0.998   | 0.189   | 2   |
| Game theory  | 1002223009      | 4.764 | 38  | 7.141   | 2.238   | 0.427   | 66  |
| Finance      | 1002301014      | 6.380 | 63  | 5.368   | 1.310   | 0.330   | 2   |
| Psychology   | 1002301008      | 3.827 | 26  | 5.008   | 0.913   | 0.204   | 59  |
| Spoken English | 1002299019    | 11.719 | 46  | 3.032   | 0.321   | 0.106   | 7   |
| Etiquette    | 1002242007      | 3.846 | 41  | 7.787   | 1.271   | 0.205   | 22  |
| C Language   | 1002303013      | 17.541 | 81  | 12.47   | 1.541   | 0.142   | 39  |
| Python       | 1002235009      | 13.417 | 53  | 10.32   | 0.896   | 0.087   | 28  |

Index a: the number of learners, b: the number of videos, c: the number of videos viewed by per learner, d: the viewing time length per learner (unit: hour), e: the time length per video (unit: hour), and f: the number of all-rounders.

Specific statistical indexes of viewing behaviors were listed in Table 1, which can be used to measure the influence of video lengths on completion rates of viewing videos. Suppose learners \{L_1, ..., L_m\} view a course with n videos \{V_1, ..., V_n\}. For each leaner \(L_s\) (s = 1, ..., m), denote the label set of he viewed videos as \(S^V_s\). For each video \(V_i\) (i = 1, ..., n), denote the label set of learners who viewed it as \(S^L_i\). Denote the time length of video \(V_i\) as \(l_i\), the time length of learner \(L_s\) viewing \(V_i\) as \(t_{is}\).

Calculate the relative viewing time length (compared with video lengths) per learner, and the number of videos viewed by per learner. Under the hypothesis that learners tend to view whole videos, the ratio between these two averages \(C_1 = (\sum_{s=1}^{m} \sum_{i=1}^{n} t_{is}/l_i) / \sum_{s=1}^{m} |S^V_s|\) measures the completion rate of viewing videos per learner. This rate can also be measured by \(C_2 = 1/n \times \sum_i \sum_{s \in S^L_i} \min(t_{is}/l_i, 1)/|S^L_i|\) at the same hypothesis. Both \(C_1\) and \(C_2\) negatively correlate to average video length (Fig. 1). In fact, human attention spans are limited. A long video is hard to attract learner attentions from beginning to end. It means a long video’s content should be carefully designed if its length cannot be shortened.
Figure 1. The negative correlation between $C_l$ ($l = 1, 2$) and average video length (unit: hour). Under the assumption that learners tend to view whole videos, the completion rate of viewing videos per learner can be measured by $C_l$ ($l = 1, 2$), which are defined in the last paragraph of Section 2.

Categorization of learners

Learners’ attention spans related to a course are different. Some are motivated to learn the whole courses, and others part of contents [19–21]. Therefore, learners can be sketchily categorized as two viewing types, namely segment-learners and potential all-rounders. Discussing the factors of dropout and engagement for segment-learners has limited insight, but is meaningful for potential all-rounders. To narrow the scope of finding potential all-rounders, we provided a non-parametric method of categorizing learners based on their viewing time length.

Table 1 showed the number of all-rounders is very small for each course. However, even the learners, who decided to complete a course, might not view all videos. For such a learner, his tenacity of viewing videos could be compared to a unit whose failure mode is of a fatigue-stress nature. The life of such a unit follows a lognormal distribution [22]. And the tenacity of a learner could be measured by his viewing time length. We labelled the learners whose viewing time length follows a lognormal distribution as lognormal-rounders. In Table 2, we provided an algorithm to recognize them. Fig. [2] showed the results of the algorithm applied to the empirical data. Specific statistical indexes of the two types of learners were listed in Table 3.
Table 2. An algorithm of categorizing learners.

Input: the viewing time length \( t_s \) and the number of viewed videos \( n_s \) of learners \( L_s \) \((s = 1, ..., m)\).

For \( k \) from 0 to \( \max(n_1, ..., n_m) \) do:

Do KS test for \( t_s \) of the learners \( L_s \) satisfying \( n_s > k \) with the null hypothesis that they follow a lognormal distribution;

Break if the test cannot reject the null hypothesis at significance level 5%.

Output: the current \( k \) (denoted as \( \kappa \)).

The unit of time is millisecond. If \( n_s > \kappa \) then \( L_s \) is labelled as a lognormal-rounder.

Table 3. Specific statistical indexes of the empirical data.

| Course      | Category | \( a \) | \( b \) | \( c \) | \( d \) | \( e \) |
|-------------|----------|--------|--------|--------|--------|--------|
| Calculus    | A        | 569    | 28.120 | 3.848  | 4.078  | 23.06  |
|             | B        | 2,386  | 3.302  | 0.319  | 1.083  | 2.385  |
| Game theory | A        | 1,522  | 16.86  | 5.919  | 3.578  | 14.13  |
|             | B        | 3,242  | 2.581  | 0.510  | 0.872  | 1.689  |
| Finance     | A        | 1,057  | 21.54  | 5.501  | 3.820  | 16.20  |
|             | B        | 5,323  | 2.157  | 0.478  | 0.602  | 1.276  |
| Psychology  | A        | 799    | 15.30  | 3.100  | 3.531  | 13.30  |
|             | B        | 3,028  | 2.294  | 0.336  | 0.648  | 1.643  |
| Spoken English | A     | 583    | 19.61  | 2.426  | 3.724  | 18.45  |
|             | B        | 11,136 | 2.164  | 0.211  | 0.636  | 1.670  |
| Etiquette   | A        | 2,084  | 12.95  | 2.213  | 3.084  | 10.80  |
|             | B        | 1,762  | 1.683  | 0.157  | 0.469  | 1.035  |
| C Language  | A        | 2,367  | 16.57  | 6.609  | 5.161  | 43.24  |
|             | B        | 15,174 | 7.147  | 0.750  | 1.827  | 5.833  |
| Python      | A        | 2,549  | 28.76  | 2.748  | 4.475  | 28.75  |
|             | B        | 10,868 | 5.600  | 0.461  | 1.791  | 5.243  |

\( A \): lognormal-learners, \( B \): other learners, \( a \): the number of learners, \( b \): the number of videos viewed by per learner, \( c \): the viewing time length per learner (unit: hour), \( d \): the entropy per learner, and \( e \): the geometric mean per learner.

MOOC attraction measurements

When a learner views a course, we can regard the video he chooses to view as a random event, and so the label of the chosen video as a random variable. When the order of course contents is ignored, the more videos a learner views, the more even his viewing time distributes, then the higher the uncertainty of which video is viewed in a viewing event is. Entropy can be used to measure the uncertainty [23]. Denote \( X_s \) to be the label of the video chosen by a viewing event of learner \( L_s \). The probability of choosing video \( V_i \) is \( p(X_s = i) = t_i / \sum_{j=1}^{n} t_j \), and so the entropy of \( X_s \) is

\[
H(X_s) = - \sum_{i=1}^{n} p(X_s = i) \log_2 p(X_s = i). \tag{1}
\]
Figure 2. The viewing time length distributions of learners. Panels showed the distributions of lognormal-learners (blue lines) and those of other learners (red lines). At significance level 5%, KS test cannot reject the null hypothesis that the viewing time lengths of lognormal-learners follow a lognormal (p-values > 0.05).

We can see that if \( L_s \) views a new video in a short time, then \( H(X_s) \) increases a little. Therefore, the number of videos viewed by \( L_s \) can be measured by \( 2^{H(X_s)} \) in a continuous way, which overcomes the shortcoming brought by the discreteness of counting viewed videos.

The entropy is free of the viewing time length \( \sum_{j=1}^{n} t_j \). However, the attraction of a course to a learner often positively correlates to the time he spent on the course. We should integrate his entropy and viewing time length into one index to measure the attraction to him. If the lengths of all videos are equal, the unit of \( 2^{H(X_s)} \) and that of the relative viewing time length \( \sum_{i=1}^{n} t_i / l_i \) are the same, namely the length of one video. Hence we can use their geometric mean as an index of measuring course attraction:

\[
I(X_s) = \left( 2^{H(X_s)} \sum_{i=1}^{n} \frac{t_i}{l_i} \right)^{\frac{1}{2}}. \tag{2}
\]

The reasonability of the formula (2) could be illustrated through following examples.

Learner \( L_s \) viewed video \( V_1 \) with time length \( t_1 = l_1 \), then his entropy \( H(X_s) = 0 \), and geometric mean \( I(X_s) = 1 \). If he viewed \( V_1 \) and \( V_1 \) with time length \( t_1 = l_1, t_2 = l_2 \), then \( H(X_s) = 1 \), \( I(X_s) = 2 \).
Figure 3. Course attraction indexes. For each course, the first two averages are calculated over all learners, and the presented index is average geometric mean \( \sum_{s=1}^{m} I(X_s)/m \).

If \( t_1 = 2l_1, t_2 = l_2 \), then \( H(X_s) = 0.92, I(X_s) = 2.38 \). If he viewed \( V_i, i = 1, 2, 3 \) with time length \( t_1 = l_1, t_2 = l_2, t_3 = l_3 \) then \( H(X_s) = 1.59, I(X_s) = 3 \). As above schematic examples showed, the geometric mean \( I(X_s) \) profiles the diminishing marginal utility in learning, because \( \partial^2 I(X_s)/\partial(t_s)^2 < 0 \).

Formula (2) also profiles the increasing process of information in the process of viewing new videos, because \( (p_1 + p_2) \log(p_1 + p_2) - (p_1 \log p_1 + p_2 \log p_2) > 0 \).

The eight courses were selected from different fields. Some popular courses, such as Python, Spoken English, can attract numerous learners. Meanwhile, some theoretical courses, e. g. Calculus, can hardly attract the learners without corresponding prior knowledge. Hence, to compare attractions of courses from different fields, it is suitable to use the average of the geometric means over all learners \( \sum_{s=1}^{m} I(X_s)/m \), which removes the heterogeneity of course learner numbers. Fig. 3 showed that this average positively correlated to the number of videos viewed by per learner and to the viewing time length per learner, which fits the common sense: view more and longer, be attracted deeper.

Now let us discuss the balance of a course’s attraction over videos. Consider a course with videos \( \{V_1, V_2, ..., V_n\} \), and denote \( l_i \) to be the length of viewing time spent by course learners on \( V_i (i = 1, ..., n) \). Then the entropy \( H = -\sum_{i=1}^{n} P(i) \log P(i) \) profiles the attraction balance of the course (Fig. 4), where \( P(i) = l_i/\sum_{j=1}^{n} l_j \). However, courses could have different video numbers. Suppose two courses’ viewing time are all distributed uniformly on videos. Then the entropy of the course with more videos is larger than that of the course with fewer videos. Therefore, to compare the attraction balances of courses, we should remove the heterogeneity of the video numbers of courses, which can be achieved by Shannon evenness \( H/\log_2 n \) [24], or by \( 2^H/n \) (Fig. 5).
Figure 4. Viewing time distributions on videos. The entropy calculated based on the viewing time distribution of a course describes the balance of the course’s attraction over videos. The more uniformly the viewing time of a course distributed, the larger the entropy is.

These indexes of Spoken English were relatively low, which is due to that 30% viewing time was attracted by one video (Fig. 3(f)). For a course, low indexes of balance imply that the course cannot attract learners persistently, and so its teachers could improve the contents of less viewed videos. Rao-Sting operator \( \Delta = \sum_{i,j} d_{ij}^{\alpha} P(i)^{\beta} P(j)^{\beta} \) (where \( \alpha = \beta = d_{ij} = 1 \) for all possible \( i \) and \( j \)) can also portray the balance of a viewing time distribution, but it does not take into account the difference of course video numbers.

Figure 5. Balance indexes of course attractions. For each course, those indexes are calculated based on the distribution of its learner viewing time.
Correlation between teaching order and viewing order

Designing teaching order is fundamental in pedagogy. MOOC education is learner-driven rather than knowledge-oriented. The correlation between teaching order and learning order affects course quality. Learning order can be reflected by viewing order, especially when learners are unsupervised. Teaching order can be expressed by video labels. If nearly viewed videos have close labels, the learning order is consistent with the teaching order. Surely, the order correlation is not meaningful to some humanities courses such as *Spoken English*, but is important to some natural science courses such as *Calculus*.

We provided a method to measure the order correlation. For each learner $L_s$, we measured the viewing correlation between any two videos $V_i$ and $V_j \in S^V_s$ (the set of videos he viewed) through $w_{ij}^s = f(|\tau^j_s - \tau^i_s|)$, where $f(\cdot)$ is a nonnegative and decreasing function, $\tau^i_s$ and $\tau^j_s$ are the start times of $L_s$ viewing $V_i$ and $V_j$ respectively. A small value of $|\tau^j_s - \tau^i_s|$ implies it is likely to exist a viewing order between $V_i$ and $V_j$.

For each video $V_i$, we calculated the weighted summation

$$\nu(i) = \frac{\sum_{s \in S^L_i} \sum_{j \in S^V_s \setminus i} w_{ij}^s}{\sum_{s \in S^L_i} \sum_{j \in S^V_s \setminus i} w_{ij}^s}.$$  \hspace{1cm} (3)

The correlation coefficient between video label and the weighted summation (3) measures the correlation between teaching order and viewing order. Here we let $w_{ij}^s = \min\left(\frac{24}{|\tau^j_s - \tau^i_s|}, 1\right)$, and calculated three widely used correlation coefficients \[26,27\] for the eight courses. Fig. 6 showed that the three correlation coefficients of *Spoken English* were relatively low, which is consistent with common senses. However, if these correlation coefficients of a mathematic course are low, then the teaching order of the course needs to be redesigned.

Note that the Pearson coefficient indicates the strength of a linear relationship between two variables $X$ and $Y$, unless the conditional expected value of $Y$ given $X$ (denoted as $E(Y|X)$) is linear or approximate linear in $X$, and verse vice. The visual examinations shown in Fig. 7 guaranteed the effectiveness of correlation analysis addressed here.

Discussion and conclusions

MOOCs are examples of learner-centered and autonomous learning. MOOC learning behaviors tend to be individual, unsupervised, and nonintervened. Human behaviors in such situations often reveal what
| Subject         | Spearman | Pearson | Kendall |
|-----------------|----------|---------|---------|
| C Language      | 0.00     | 0.20    | 0.40    |
| Python          | 0.00     | 0.20    | 0.40    |
| Spoken English  | 0.00     | 0.20    | 0.40    |
| Etiquette       | 0.00     | 0.20    | 0.40    |
| Psychology      | 0.00     | 0.20    | 0.40    |
| Finance         | 0.00     | 0.20    | 0.40    |
| Calculus        | 0.00     | 0.20    | 0.40    |
| Game theory     | 0.00     | 0.20    | 0.40    |

**Figure 6. Correlation between teaching order and learning order.** Teaching order is expressed through video labels, and learning order is expressed by viewing order. The correlation is measured by three typical correlation coefficients between variable pair \( i \) and \( \nu(i) \) (Eq. 3).

**Figure 7. The conditional expected value of \( \nu(i) \) given video label \( i \).** The approximatively linear trend of \( E(\nu(i)|i) \) guaranteed the effectiveness of correlation coefficients in Fig. 5.
they are. Therefore, one could have faith in the reliability of viewing behavior data. We employed viewing behavior data to categorize learners, to assess course attractions and the correlations between teaching order and learning order. The practicability of our methods is validated with the empirical data provided by iCourse. Our results help to understand the rules of human cognition behaviors on the Internet.

Our methods need further improvement. In terms of data application, learning preferences should be addressed in learning pattern recognition, which helps teachers to implement individualized education. In terms of pedagogy, studying autonomous and learner-centered MOOC learning helps the development of constructivism theory \[28,29\] and provides cases for online pedagogy. In terms of data fusion, testing and certificating behaviors should be considered in MOOC profile, which contribute to assess learning achievements. The analysis of correlations between these behaviors and viewing behaviors helps to inference the achievements of the learners without certifications and test scores.

We finished our study by asking a question: How to assess MOOCs. The indexes to assess traditional courses are inappropriate for profiling MOOC quality such as course completion rate \[30\]. It is, therefore, necessary to design new indexes to assess MOOCs in their own way. Assessing a course is in essence to determine the degree to which its teaching reaches its goal \[31\], and so inextricably connects with learning quality of its learners \[32\], learner engagements \[33,34\], learning patterns \[35–37\], and achievements \[38,39\]. Therefore, learning achievements contributes to MOOC quality, and so our results have potential to be indexes of MOOC assessments.

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