What Are MOOCs Learners' Concerns? Text Analysis of Reviews for Computer Science Courses

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Abstract. In MOOCs, course reviews are valuable sources for exploiting learners' attitudes towards the courses provided. This study employed an innovative structural topic modeling technique to analyze 1920 reviews of 339 courses regarding computer science to understand what primary concerns the learners had. Nine major topics, including *course levels*, *learning perception*, *course assessment*, *teaching styles*, *problem solving*, *course content*, *course organization*, *critique*, and *learning tools and platforms* were revealed. In addition, we investigated how the identified nine topics varied across reviews with different ratings. Results indicated that negative reviews tended to relate more to issues such as *course assessment*, *learning tools and platforms*, and *critique*, while positive reviews concerned more about issues such as *course levels*, *course organization*, and *learning perception.* This study provided tutors with novel implications for developing online courses, particularly computer science courses.

Keywords: MOOCs · Online course reviews · Structural topic model

1 Introduction

Massive open online courses (MOOCs) possess significant potential to enable every learner to access to high-quality educational resources. Since the appearance of the first open online course in 2011, there has been an increasing interest in MOOCs worldwide [1–3]. With the continuous growth in the interest of MOOCs, many colleges have been encouraged to launch online courses. According to Shah (2018) [4], there have been 11,400 MOOCs offered by over 900 colleges worldwide till 2018, with an enrollment of about 101 million online learners. Practitioners and educators have been very interested in the determination of how successful the MOOCs they launched [5].

Compared with face-to-face interviews, it is more convenient to use MOOCs in terms of collecting and storing learners' comments, and the quality and usability of the data

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collected can be ensured. A number of previous studies have concerned about structured data analysis, for example, learners' clicks and grades [6, 7]. Nevertheless, unstructured textual data collected using interactive technologies, for example, discussion forums and online course reviews, remained to be explored [8, 9]. Course reviews offer an abundant source of information regarding learners' opinions towards issues such as course contents, instructors, and course platforms [10]. For example, Hew (2016) [11] conducted an inductive iterative coding method on comments of 965 participants in three top-rated MOOCs courses to uncover causes for their popularities. Five factors were revealed, including problem-centered learning, tutor accessibility and enthusiasm, active learning, peer interaction, and supportive learning resources. However, the processes and findings by using the manual coding method heavily depend on the expertise of human coders [12]. Besides, subjective biases result in the difficulty in replicating the findings. In addition, the sample sizes are limited [13].

With the advance of computer-based text analysis methods, this study sought to explore reviews comments of computer science MOOCs courses by the use of topic modeling, an automatic approach that has become increasingly popular for analyzing large-scale textual data in recent years [14–17]. For example, Chen et al. (2020) [18] presented a thorough review of *the British Journal of Educational Technology* during the period 1971–2018, with the adoption of bibliometrics and topic models. Xie et al. [19] reviewed studies concerning personalized learning collected from the Web of Science by adopting a coding scheme proposed with the basis of the constructivism theories.

The goal of this study was to analyze 1920 reviews for 339 courses concerning computer science to understand what primary concerns the MOOCs learners had, with the adoption of an innovative structural topic modeling technique [20, 21]. In addition, we further investigated how the identified nine topics varied across reviews with different ratings.

2 Materials and Methods

The flow chart of data collection and analyses is described as Fig. 1, including data acquisition, data preparation, and structural topic modeling, as elaborated in the following sections.

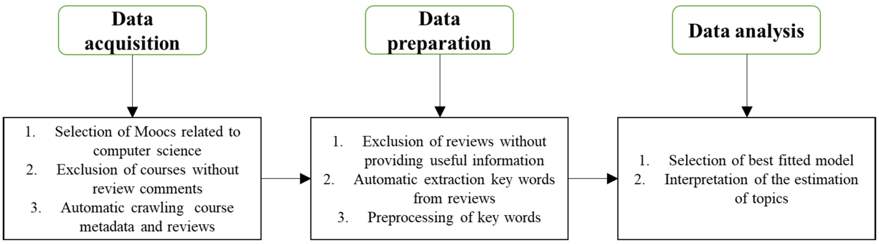

Fig. 1. Flow chart of data collection and analyses

2.1 Data Acquisition and Preparation

The procedure of data acquisition and preparation was as follows. The online course reviews were collected using Class Central[1], one of the best-known MOOCs review sites worldwide. It had been used in a number of studies [22, 23]. We first selected MOOCs in the category of computer science, after removing duplicates as well as excluding those without review comments, 339 unique MOOCs remained. We then created a web crawler program to automatically crawled course metadata as well as corresponding review comments. Besides, we excluded reviews without providing useful information, for example, "A completed this course," "B is taking this course right now," and "C completed this course. Person found this review helpful." Finally, 1920 reviews for 339 courses in relation to computer science were used for topic modeling and analyses (Table 1).

Table 1. Statistics of the review dataset.

Items	Frequency	Percentage
Distribution of course grade (number of courses)		
Grade 1	20	5.90%
Grade 2	24	7.08%
Grade 3	45	13.27%
Grade 4	109	32.15%
Grade 5	141	41.59%
Distribution of course grade (number of reviews)		
Grade 1	177	9.22%
Grade 2	96	5.00%
Grade 3	94	4.90%
Grade 4	321	16.72%
Grade 5	1232	64.17%

2.2 STM Model Setup

The 1920 review comments were used for STM modeling. First, extract key terms from comments with the adoption of natural language processing. Second, unify terms with similar meanings. For example, organize, organized, and organizing were all unified as organize. Third, remove stop words (e.g., the, is, you, a), punctuations, and numbers.

[1] https://www.class-central.com/.

Fourth, remove meaningless words, for example, add, get, one, lot, let, something, someone, sometimes, take, and anyone. Fifth, filter unimportant words using term frequency-inverse document frequencies (TF-IDF). We empirically excluded terms with a TF-IDF value of less than 0.05. We then ran several models, with the number of topics ranging from three to 25. Two domain experts independently carried out comparisons of the results of the 23 models, and a nine-topic model was selected as the final model.

3 Results

3.1 Topic Interpretation

Table 2 displays the nine-topic STM results, together with the representative terms, topic proportions, as well as suggested topic labels. The top four topics being the most frequently mentioned in review comments included *Course organization* (18.41%), *Course levels* (17.29%), *Learning perception* (13.42%), and *Problem solving* (12.00%). The other five topics were *Course content* (8.47%), *Learning tools and platforms* (8.31%), *Course assessment* (8.09%), *Critique* (7.17%), and *Teaching style* (6.83%).

Table 2. Topic summary.

Topic label	Topic proportion	Top words
Course levels	17.29%	Difficulty, medium, hour, spend, easy, hard, beginner
Learning perception	13.42%	Goodpretty, technical, introduction, clear, inspire, knowledge, overview
Course assessment	8.09%	Answer, unit, install, question, search, staff, figure, code, engine, wrong, final, solution, exam
Teaching style	6.83%	Didactic, interesante, informatics, explicate, explication, innovation, profound
Problem solving	12.00%	Programming, challenge, solve, assignment, algorithm, problem, note
Course content	8.47%	Regression, graphlab, analytics, classification, clustering, machine, neural
Course organization	18.41%	Creative, organize, fun, awesome, field, session, task
Critique	7.17%	Reversible, energy, computation, talk, free, poor, waste
Learning tools and platforms	8.31%	Git, github, watch, web, video, java, tool

3.2 Topic Distribution Across Negative and Positive Reviews

We further investigated how the identified nine topics varied across reviews with different ratings. As shown in Fig. 2, negative reviews tended more to be related to issues such as *Course assessment*, *Learning tools and platforms*, and *Critique*, while positive reviews concerned more about issues such as *Course levels*, *Course organization*, and *Learning perception.* In addition, there were two topics, that is, *Course content* and *Problem solving*, tended to be equally concerned for both negative and positive reviews.

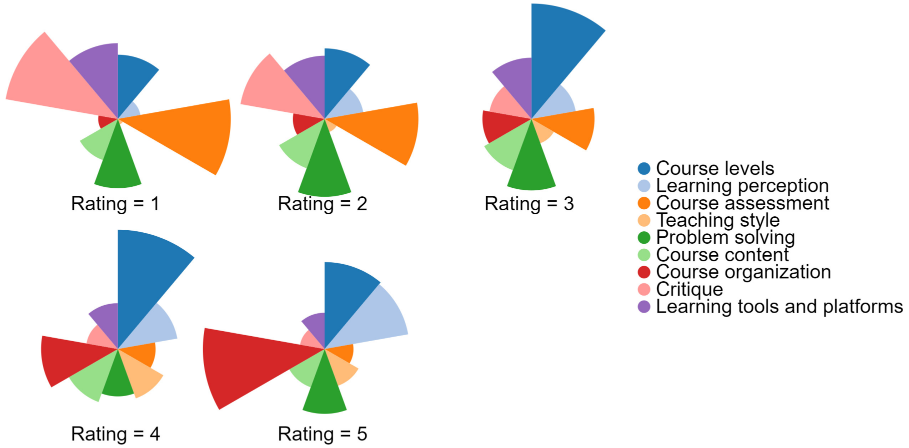

Fig. 2. Topic distributions across reviews with different ratings.

4 Discussion and Conclusion

This study analyzed 1920 reviews for 339 courses concerning computer science with the use of structural topic modeling, to understand what primary concerns the MOOCs learners had. We additionally investigated how the identified nine topics varied across reviews with different ratings. We empirically proved the effectiveness of the application of structural topic modeling of online course reviews. In particular, comments with high proportions to a particular topic were exactly relevant. For example, for the topic *Course levels*, examples of highly relevant review comments were as follows:

> "spending 5 h a week on it and found the course difficulty to be hard. good course but was hard i think that could also be Very hard."
>
> "spending 3 h a week on it and found the course difficulty to be easy. I made another dream come true - I've finished another Dr. Chuck's course! It appeared to be a lot better than I thought it to be. Really enjoyed it. It is useful and thought-provoking. Thank you, Dr. Chuck for all this!"

Second, for the topic *Learning perception*, examples of highly relevant review comments were as follows:

> "Excellent course. Cleanly separates the different pieces that go into making bitcoin, and explains each of them simply and clearly. Covers not only bitcoin and cryptocurrencies, but also the wider implications and applications of the blockchain to non-currency applications. Highly recommended for anyone interested in bitcoin or the blockchain."

Third, for the topic *Course assessment*, examples of highly relevant review comments were as follows:

> "It's super buggy and totally frustrating. I got to the very last segment before I realized that my assignments did not even submit totally, and I made sure to go through the exact procedures completely."
>
> "The course videos itself are moderately interesting, but the quizes are very bad. The questions are not clear at all and can be interpreted in different ways. It's frustrating to lose points because the questions are so confusing."

In addition, for the topic *Course content*, examples of highly relevant review comments were as follows:

> "This was certainly a practical overview of machine learning techniques. There was very little discussion of the algorithms behind these techniques, certainly much less than even in Andrew Ng's Coursera course, which is itself supposedly fairly watered-down compared to many…"

This study provided tutors with novel insights into the design and improvement of online courses, particularly computer science courses. Regarding future research, there are three directions worth investigating. First, further investigation can be considered by defining negative and positive reviews [24] to explore which topics are more likely to appear in negative reviews. Second, the occurrence of these topics is also worth investigating. Besides, further investigation is encouraged to incorporate course metadata (e.g., course schedule and course duration) and learner metadata (e.g., course completion status) to explore factors affecting learners' satisfaction. In addition, future investigation using learning analytics to propose tools or systems for obtaining a better learning experience is also encouraged (e.g., [25]).

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