Analysis Method for Teacher-Student Interaction in Online English Courses

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Abstract—In online learning, the teacher-student interaction mainly takes place in the form of themed discussion anytime, anywhere, and the posting and commenting on the theme. It is of great practical significance to select a proper behavior analysis method that effectively analyzes the mass data on teacher-student interaction. Taking online English courses as an example, this paper explores the teacher-student interaction during online learning. Firstly, the ant colony algorithm was adopted for cluster analysis of teacher-student interaction, and the analysis procedure was detailed. Next, the features of teacher-student interaction were illustrated from three aspects, namely, overall interaction on online learning platform, progress of themed discussion, and teacher-student interaction, in order to examine the teacher-student interaction model. Finally, the features were obtained for teacher-student interaction in themed discussion of online English courses.

Keywords—online learning, English courses, analysis on teacher-student interaction

1 Introduction

Online classroom is the most important place for teacher-student interaction [1-4]. Due to the flexibility and course diversity of online learning, there is a continuous growth of teacher-student interaction information of online learning [5-8]. In online learning, the teacher-student interaction mainly takes place in the form of themed discussion anytime, anywhere, and the posting and commenting on the theme, instead of the traditional face-to-face interaction [9-15]. It is of great practical significance to select a proper behavior analysis method that effectively analyzes the mass data on teacher-student interaction, which would improve the teacher-student interaction of online learning.

To build an interaction model for oral language teaching, Mulyani [16] adopted the realistic ethnographic method, and carried out data analysis according to Miles, Huberman's interactive model. The results show that the teaching and learning interaction models of four colleges for oral language teaching are mainly controlled by the lecturer. The interactive discussion of online learning is much more complex than that of traditional education. Mohammad et al. [17] introduced and analyzed the types, methods, and e-learning tools for interaction. The survey results show that students and teachers can benefit from the methods and tools, and overcome the challenges of e-transaction between them. In the classroom environment, the teachers are generally concerned with interaction, while the students lack interaction with teachers, and fail to react to the teachers' classroom dialog. Doroja et al. [18] tried to enhance and create a more interactive learning environment through mobile communication, thereby improving the learning process. New Zealand encourages teachers to enter the practical community, and provide a real learning experience. Slatter and France [19] provides information about teacher-student interaction, and explained how this kind of contact affects student education. Two interactive strategies were given: student-controlled interaction, and teacher-controlled interaction. There are few studies on the types of interaction occurring when teachers attend the dialog groups of students. Robles et al. [20] probed deep into the students' views of WhatsApp and their acceptance of the academic usage of the tool. Besides, they analyzed different kinds of interaction, with a chat record as an example. The results show that, to promote learning, the different student-teacher interactions should not merely focus on knowledge construction.

Overall, the existing studies have explored the participation level, and interactive level of teacher-student interaction of online courses. The relevant results are of reference value, but cannot be directly applied to domestic online courses. In addition, it is not highly referential to analyze a single kind of teacher-student interaction, for the teacher-student interaction data vary with the types of online learning courses. Taking online English courses as an example, this paper explores the teacher-student interaction during online learning. Section 2 adopts the ant colony algorithm for cluster analysis of teacher-student interaction, and details the analysis procedure. Section 3 illustrates the features of teacher-student interaction from three aspects, namely, overall interaction on online learning platform, progress of themed discussion, and teacher-student interaction, and displays the architecture of the analysis system for the teacher-student interaction model. Finally, experiments were carried out to obtain the features for teacher-student interaction in themed discussion of online English courses.

2 Cluster analysis

This paper divides teacher-student interaction of online learning into four categories: teacher-dominated, antagonistic, collaborative, and student-dominated. The four categories were further split into eight small classes: strict requirements, dominance of knowledge teaching, cooperation, interaction, autonomous thinking, autonomous learning, dissatisfaction, and learning disorder (Figure 1).

Based on ant colony algorithm, teacher-student interaction was subjected to cluster analysis. Following the principle of the original ant colony algorithm, the mathematical model of that algorithm was further analyzed for the analysis on teacher-student interaction. The details of the analysis on teacher-student interaction are as follows.

Let A be a vertex; U=(1, 2, ..., m) be the set of vertices. Then, a weighted graph is constructed as Ω=(U, A). The distance between vertices is denoted as c_{li}, which is greater than zero, and approaches ∞ (l, $i \in U$). Then, the following binary function can be established:

$$y_{li} = \begin{cases} 1, if \ \ (l,\ i) \ is\ on\ the\ selected\ path \\ 0, otherwise \end{cases} \tag{1}$$

Let $|Q|$ be the number of vertices of graph Ω within set Q. Then, the solutions meeting the constraint can form a mathematical planning model for the Hamiltonian path:

$$\min X = \sum_{l=1}^{n}\sum_{i=1}^{n} c_{li} y_{li} \tag{2}$$

$$s.t \begin{cases} \sum_{i=1}^{m} y_{li} = 1, l \in U \\ \sum_{l=1}^{m} y_{li} = 1, i \in U \\ \sum_{l \in p}\sum_{i \in p} y_{li} \le |Q| - 1, \forall Q \subset U \\ y_{li} \in \{0,1\} \end{cases} \tag{3}$$

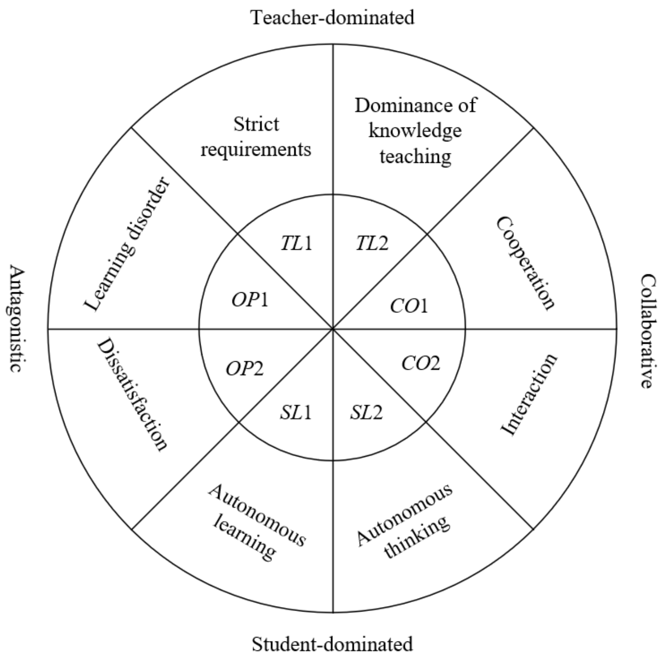

Fig. 1. Teacher-student interaction model

Let $\varsigma_{li}(q)$ be the amount of pheromone; $AV_z=\{U - TL_z\}$ be the set of all vertices; $a_l(q)$ be the number of ants; B be the total number of ants; β be the coefficient of residual pheromone; γ be the coefficient of visibility; $\varphi_{li}(q)=1/c_{li}$ be the heuristic function; TL_z (z =1, 2, ..., B) be the tabu list of the vertices traversed by ant z. Then, the transfer probability $s^z_{li}(q)$ from vertex l to the adjacent vertex i can be calculated by:

$$s_{li}^{z}\left(q\right)=\begin{cases}\dfrac{\left[\varsigma_{li}\left(q\right)\right]^{\beta}\left[\phi_{li}\left(q\right)\right]^{\gamma}}{\sum\limits_{o=AV_z}\left[\varsigma_{lo}\left(q\right)\right]^{\beta}\left[\phi_{lo}\left(q\right)\right]^{\gamma}}, i\in AV_z\\ 0, other\end{cases} \tag{4}$$

Let $\sigma \in [0, 1]$ be the volatility coefficient; $\Delta\varsigma_{li}(q)$ be the pheromone increment on a path. Based on the principle of pheromone volatilization, the historical pheromone can be adjusted by:

$$\varsigma_{li}\left(q+1\right)=\left(1-\sigma\right)\varsigma_{li}\left(q\right)+\Delta\varsigma_{li}\left(q\right) \tag{5}$$

$$\Delta\varsigma_{li}\left(q+1\right)=\sum_{z=1}^{B}\Delta\varsigma_{li}^{z}\left(q\right) \tag{6}$$

The ant colony algorithm solves the analysis on teacher-student interaction in the following steps:

1. Initialize the ant colony, set the current number of iterations to 0, denote the maximum number of iterations as Nmax, and place B ants randomly at the m vertices of the weighted graph.
2. Initialize the pheromone matrix, and define ςli (0) as a constant.
3. Initialize the tabu list TLz, and save the starting vertices of the ants.
4. Compute the structural solution corresponding to each ant, and update TLz until the list is filled up.
5. Update the pheromone concentration Δςzli (q) on each path, and complete the evaluation of the ant colony.
6. Judge whether the maximum number of iterations N_{max}, or the preset error is reached. If yes, terminate the iterations, and output the optimal solution. Otherwise, empty TL_z, and jump to Step 2.

This paper discusses the ant colony algorithm, which is inspired by ant foraging behavior, aiming to classify the image of teacher-student interaction into independent and tight classes. Let $Y=\{Y_l|l=1, 2, ..., M\}$ be the set of M data samples; $Y_l=\{y_{l1}, y_{l2}, ..., y_{lz}\}$ be a z-dimensional vector; Z be the number of classes; $c_{lz}=c(Y_l, n_z)=(\Sigma^x_{i=1}|y_{li}-n_{zi}|^2)^{1/2}$ be the Euclidean distance, i.e., the distance from sample Y_l to cluster center $n_z=(n_{z1}, n_{z2}, ..., n_{zx})$; h_{lz} be the membership of Y_l relative to N_z. Then, the objective function F of the algorithm can be defined as:

$$\min OF = \sum_{z=1}^{Z}\sum_{l=1}^{M} h_{lz} c_{lz} \tag{7}$$

$$s.t \begin{cases} \sum_{z=1}^{Z} h_{lz} = 1, l = 1, 2, ..., M \\ \sum_{l=1}^{M} h_{lz} \geq 1, z = 1, 2, ..., z \end{cases} \tag{8}$$

Let N_z be the *z*-th class. The membership h_{lz} can be expressed as:

$$h_{lz} = \begin{cases} 1, Y_l \in N_z \\ 0, Y_l \notin N_z \end{cases} \tag{9}$$

Let $\varsigma_{lz}(q)$ be the residual pheromone concentration on the path n_z from sample Y_l to cluster center n_z after the q-th iteration; OF_j be the minimum of the objective function; $\Delta\varsigma^j_{lz}=1/OF_j$; J be a constant; σ be the volatility coefficient. Then, the pheromone concentration on each path can be calculated by:

$$\varsigma_{lz}(q+1) = (1-\sigma)\varsigma_{lz}(q) + \sum_{j=1}^{J} \Delta\varsigma_{lz}^{j} \tag{10}$$

The specific steps of ant colony algorithm are as follows:

1. Initialize the ant colony, and configure parameters σ, t_0, J, s_p, Z, B, and N_{max}.
2. Initialize pheromone matrix, and define ς_{li} (0) as a constant.
3. Assign a random number λ to each ant. If λ is smaller than the preset value λ_0, choose the class with the highest pheromone concentration, and allocate sample Y_l to class N_z. Otherwise, randomly allocate sample Y_l to class N_z, using the regularized probability formula $s_{lz}=\varsigma_{lz}/\Sigma^{Z}_{z=1}\varsigma_{lz}$, z=1, 2, ..., Z.
4. Compute the cluster head according to the structural solution corresponding to each ant, i.e., find the mean attribute of samples in each class. Meanwhile, calculate the value of the objective function OF.
5. After constructing all structural solutions, rank the objective function values in descending order, and perform simple local search of the top J solutions.
6. Compute and update the global pheromone concentration on each path.
7. Judge whether the maximum number of iterations N_{max}, or the preset error is reached. If yes, terminate the iterations, and output the optimal solution. Otherwise, set q=q+1, and jump to Step 2.

The flow of the clustering method is illustrated in Figure 2.

The above algorithm was adopted to perform cluster analysis on teacher-student interaction data, and plot an image for teacher-student interaction, laying the basis for further analysis on the features of teacher-student interaction.

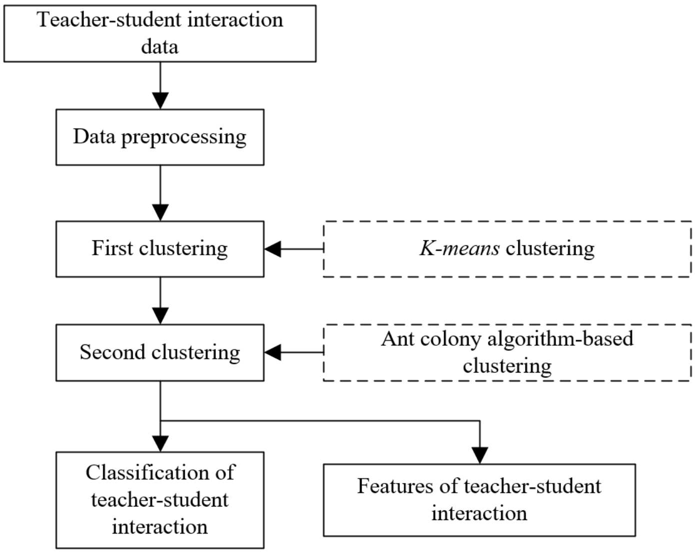

Fig. 2. Flow of the clustering method

3 Interaction model analysis

To analyze the teacher-student interaction of online English courses, it is necessary to depict the interaction with proper features. This paper tries to complete the depiction from three aspects: overall interaction on online learning platform, progress of themed discussion, and teacher-student interaction. Figure 3 shows the architecture of the analysis system for teacher-student interaction model.

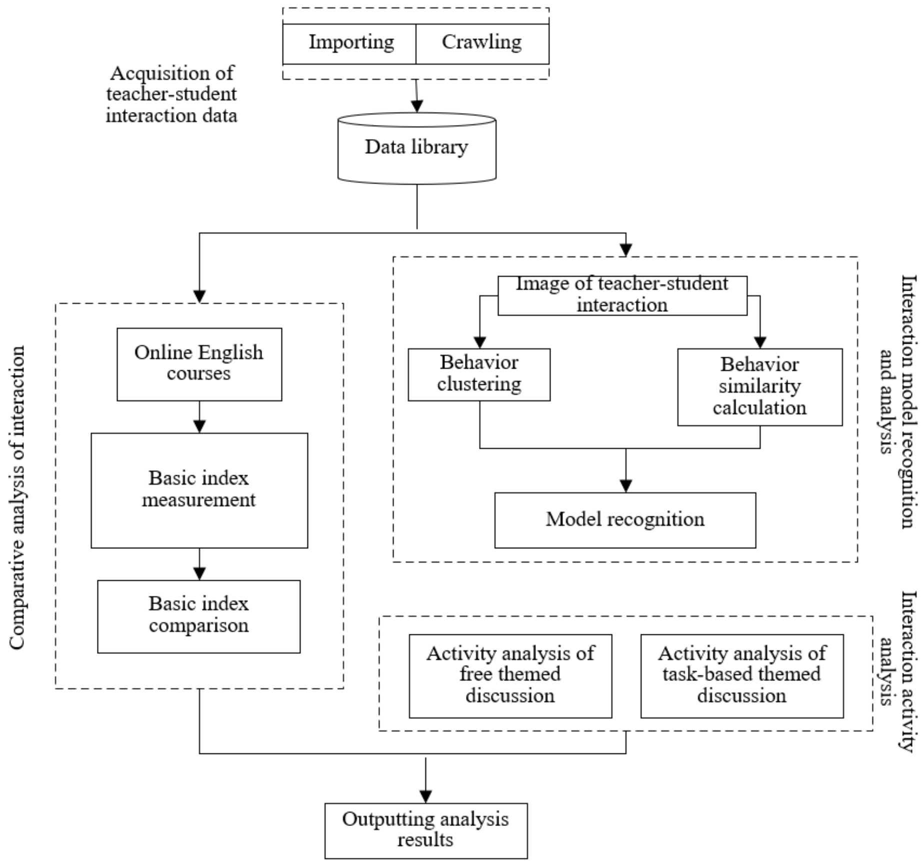

Fig. 3. Architecture of the analysis system for teacher-student interaction model

Tables 1 and 2 show the teacher interaction indices and student interaction indices in themed discussion, respectively. Let *PV* be the students' posting progress vector; *ST* be the start time of the course; *ET* be the end time of the course; *DT* be the posting time of the l-th post. Then, the posting feature v_l of students in *PV* can be calculated by:

$$v_l = \frac{DT - ST}{ET - ST} \tag{11}$$

Table 1. Teacher interaction indices in themed discussion

Serial number	Meaning	Formula
TI-1	Mean posting speed of teachers	Number of posts of teachers / Course duration
TI-2	Online time of teachers	Online time of teachers / Course duration
TI-3	Proportion of posts of teachers	Number of posts of teachers / Total number of posts
TI-4	Proportion of replies of teachers	Number of replies of teachers / Total number of replies

Table 2. Student interaction indices in themed discussion

Serial number	Meaning	Formula
SI-1	Mean posting speed of students	Number of posts of students / Course duration
SI-2	Online time of students	Online time of students / Course duration
SI-3	Proportion of posts of students	Number of posts of students / Total number of posts
SI-4	Proportion of replies of students	Number of replies of students / Total number of replies

Let m be the number of students' posts; y_l be the number of teachers' replies $Y(y_1, y_2, ..., y_m)$ to the l-th post. Then, the teachers' reply rate to students' post can be calculated by:

$$RR(Y)=\frac{\sum y_l}{m}*100\% \tag{12}$$

Based on the value of RR(Y), the activity of free themed discussion can be measured.

Suppose course A has 1,000 speakers in themed discussion. After obtaining the image of teacher-student interaction, the features were selected for computing the similarity of interaction behaviors. The selection criterion is denoted as $\Psi1(\phi1, \phi2, \phi3, \phi4, \phi5, \phi6, \phi7, \phi8, \phi9, \phi10)$. By computing the similarity between $PV_1, PV_2, ..., PV_{1000}$ and the criterion, the similarities $G_1, G_2, ..., G_{1000}$ can be obtained. Next, the number of students with G_l greater than threshold υ is calculated. After that, the proportion of students with G_l greater than threshold υ can be obtained by:

$$SP=\frac{COUNT}{1000}*100\% \tag{13}$$

If SP is greater than threshold ε, then the teacher-student interaction in themed discussion of course A is driven by task; otherwise, the interaction is free.

The pre-clustering data of teacher-student interaction are not labeled. Hence, the clustering effect cannot be measured by comparison with the original labels. This paper chooses the Calinski-Harabasz index, which does no require labels to evaluate clustering effect, to assess the clustering effect of our model. Let n be the number of data samples; Z be the number of classes of the data after clustering; B_e and W_e be between-class and intra-class covariance matrices, respectively; ψ be the trace of mean values. Then, the score of the *Calinski-Harabasz* index can be calculated by:

$$t(e)=\frac{\psi(B_e)}{\psi(W_e)}*\frac{n-Z}{Z-1} \tag{14}$$

Formula (14) shows that the greater the covariance between different classes of teacher-student interaction, the smaller the covariance between the samples in the same class, the larger the score t, and the better the clustering effect of teacher-student interaction.

4 Experiments and results analysis

Figure 4 shows the students' posts in themed discussion, where the x-axis and y-axis represent the time interval and student number, respectively. It can be seen that the student serving as teaching assistant posted in almost every time interval. The data on this student must be removed before analyzing the teacher-student interaction model in themed discussion.

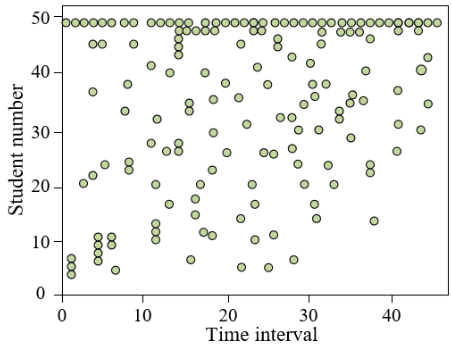

Fig. 4. Students' posts in themed discussion

Figure 5 shows the clustering results of teacher-student interaction in online English courses. The interaction data were clustered into eight classes. The different types of data were clearly differentiated. The Calinski-Harabasz index of the clustering model was relatively high. The centroid vector of each class helps to judge whether the teacher-student interaction is free or task-driven. Using the overall image of teacher-student interaction in themed discussion of online English courses, the features of the interaction can be obtained (Table 3).

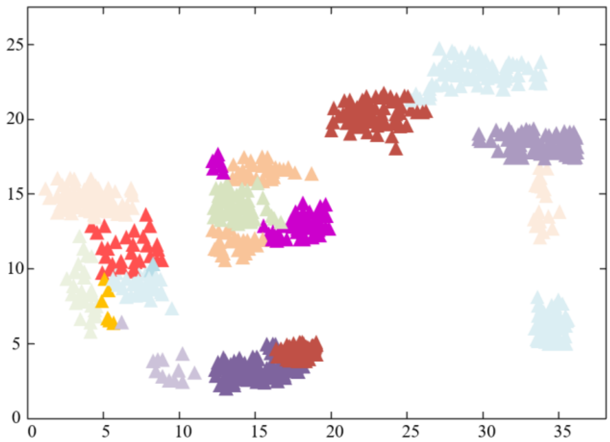

Fig. 5. Clustering results

Table 3. Overall features of teacher-student interaction in themed discussion

Name of feature	Mean	Median	Maximum	Minimum	Standard deviation
Number of teachers' posts	4	4	12	2	1.15
Number of teachers' replies	144.62	135	452	70	3.68
Time difference between the date of the most posts and the start time of the course	6	-0.15	36	-0.2	2.62
Number of posts on the date of the most posts	5	6	12	4	0.42
Time difference between the date of the most replies and the start time of the course	19.26	22	34	-0.2	11.58
Number of replies on the date of the most replies	275	255	452	157	2.37
Sum of the number of replies per teacher	6	5	18	4	3.28
Sum of the number of replies per student	24	22	53	19	1.74

As shown in Table 3, in the themed discussion, the number of teachers' posts averaged at 4, the number of teachers' replies averaged at 144.62, the time difference between the date of the most posts and the start time of the course averaged at 6, the number of posts on the date of the most posts averaged at 5, the time difference between the date of the most replies and the start time of the course averaged at 19.26, the number of replies on the date of the most replies averaged at 275, the sum of the number of replies per teacher averaged at 6, and the sum of the number of replies per student averaged at 24. These preliminary results show that the teachers made many replies in the themed discussion of online English courses, suggesting that different teachers posted and replied similar number of posts on average.

Figure 6 draws the relationship between teachers' posts and students' replies. It can be seen that the themed discussion had nearly 420 students' replies and 13 teachers' posts. About ¾ of all students (35) replied the eight posts by teachers. The proportion shows that no teacher published task-based posts in the themed discussion.

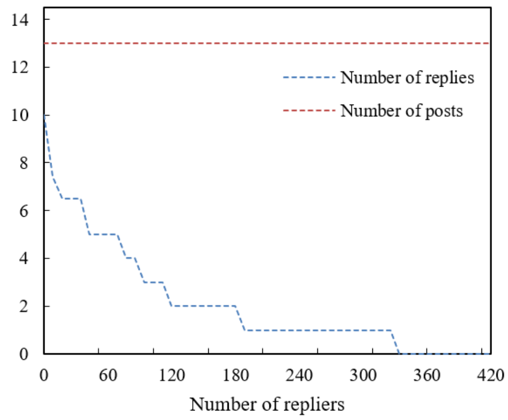

Fig. 6. Relationship between teachers' posts and students' replies

Table 4 shows the distribution of teachers replying to the themed discussion of the same course in different time intervals. Among the six teachers, two replied after 0.25h, and 4 replied within 0.1h. In general, the teachers completed the reply task well, judging by the response time. This means the themed discussion of the online English course remains active. Figure 7 shows the proportion of teachers and students posting in different themed discussions. It is clear that the teachers and students collaborated in online learning, and achieved an excellent interaction effect.

Table 4. Distribution of teachers making replies in different time intervals

Teacher number	≤0.1	0.1-0.2	0.2-0.3	0.3-0.4	0.4-0.5	≥0.5
*TEA*1	2015	2	1	1	0	0
*TEA*2	3284	0	0	0	2	1
*TEA*3	3748	0	1	705	638	2
*TEA*4	3912	2	6	128	125	1
*TEA*5	1649	8	1253	74	72	3
*TEA*6	1527	1625	2516	58	55	4

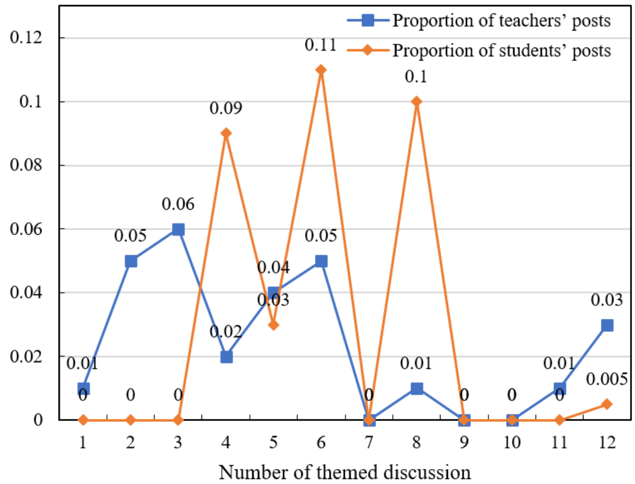

Fig. 7. Proportion of teachers and students posting in different themed discussions

5 Conclusions

Taking online English courses as an example, this paper explores the teacher-student interaction during online learning. Firstly, the authors adopted the ant colony algorithm for cluster analysis of teacher-student interaction, and detailed the analysis procedure. Then, the features of teacher-student interaction were depicted in three dimensions: overall interaction on online learning platform, progress of themed discussion, and teacher-student interaction, and the teacher-student interaction model was analyzed in details. Through experiments, the authors summarized students' posts in themed discussion, obtained the clustering results of teacher-student interaction in online English courses, and gathered the overall features of teacher-student interaction in themed discussion. The data on different types of interaction were found to be clearly different. After that, the relationship between teachers' posts and students' replies was plotted, which shows that no teacher published task-based posts in the themed discussion. Finally, the authors displayed the distribution of teachers replying to the themed discussion of the same course in different time intervals, and the proportion of teachers and students posting in different themed discussions. The results show that teachers and students collaborated in online learning, and achieved an excellent interaction effect.

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