

THE STUDY OF KNOWLEDGE DIFFUSION BASED ON COMPLEX NETWORKS

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ABSTRACT

We study the knowledge diffusion and students participation in MOOC forum and face-to-face discussion on SPOC. A multi-layers networks model which is based on BA scale-free networks and NW model is shown to explore how the social competence and different absorptive capacity of face-to-face individuals on SPOC, the proportion of contributors of MOOC forum and the complexity of knowledge effect the participation and knowledge diffusion of the online forum. In this paper, we find that: the greater the proportion of online contributors, the more conducive to the dissemination of online knowledge, the higher online participation; The social competence, different average absorptive capacity of offline individuals and knowledge complexity have no significant impact on forum participation; different distribution of offline absorptive capacity will affect the average level of knowledge online to a certain extent; And, the higher the complexity of knowledge, the less conducive to knowledge transfer.

KEYWORDS: *Knowledge Diffusion, Complex Network, Participation*

Article History

Received: 30 Apr 2019 / Revised: 08 May 2019 / Accepted: 15 May 2019

INTRODUCTION

With the rapid development of current computer technology and cloud technology, the dissemination of knowledge has become more convenient and flexible. The dissemination of knowledge can achieve cross-regional communication and is no longer limited by time and space as before. Traditional education and teaching activities are often limited by time and space, and the emergence of WEB2.0 and cloud service platforms are making these restrictions gradually weakened. Since 2012, MOOC (large-scale open online courses), led by Stanford University, Harvard University, and other educational institutions, many domestic universities have also begun to enter the MOOC for online education. When education and the "Internet +" era are combined, this provides new exploration and research content for education and teaching activities and the dissemination of knowledge.

MOOC is characterized by large-scale, open, flexible use and rich teaching content. At MOOC, learning individuals can acquire knowledge through instructional videos, classroom exercises, forum discussions, unit tests, etc. Unlike traditional education, the individual learning on MOOC can be anyone, so the learning individuals on MOOC have larger Individual differences.

In traditional college education, some colleges and universities cooperated with MOOC to carry out SPOC course teaching. The SPOC course, which is a private course, is a credit-based course. The course generally has threshold requirements for the individual who chooses the course (for example, the same class, major, etc.), which includes online learning and regular teacher-student meetings. It is a mixed form of learning.

The open nature of MOOC's large-scale online has also brought many problems to the learning of MOOC: in the case of high registration rate, the completion of the MOOC course is often low. The investigation by Liu^[1], Jordan and Jiang^[2],³ et al. proved the existence of this phenomenon.

At present, foreign scholars have made many contributions in MOOC research, and their research directions can be roughly divided into the following categories^[4]:

- Using cluster analysis to analyze the types of learning individuals on the MOOC platform^[5]. Kizilce et al.^[6] divided learners into observers, finishers, early adopters, and exiters. Ferguson et al. (2015) classify MOOC learners into two categories: auditors and finishers. Rodrigues et al. (2016) divided forum learners into learning participants, occasional participants, and non-participants.
- Research on the motivation of learning individual behavior. Fang Xu^[7] proposed the TAM3 model to study the influencing factors of learning behavior; GS. Stump et al. developed a classification framework based on the classification of forum content^[8].
- Study the completion of individual courses, the rate of returning, and the results. D. Yang et al. studied the influence of social interaction on the online course^[9]; Taylor et al.^[10] studied the influencing factors of learners' withdrawal from learning based on data mining and analysis. Zong Yang^[11] used logistic regression analysis to explore the impact of learning behavior on academic performance.

However, there are few research articles on the knowledge dissemination between SPOC and MOOC, and there are few empirical studies, questionnaires, etc. As for the issue of how the knowledge of SPOC and MOOC platforms is spread, there are no clear research results. Will the learning or social behavior of individuals affect the dissemination of knowledge on the MOOC in which they are located? Will it affect the participation of online MOOC forum? What behavioral factors are there in the offline SPOC individuals that lead to the participation of learning individuals on the MOOC in online forums? These problems have not yet been clearly studied and results. Therefore, this paper attempts to establish a knowledge spillover model based on complex networks to briefly study the above problems.

The Model

Underlying Network Selection

MOOC Forum Network

This paper argues that the forum learning network on the MOOC is similar to the BA scale-free network. Among them, the nodes on the BA scale-free network represent the learners of the online forum. In order to simplify the model, this paper does not consider the directionality of the edge: if the post published by node A is browsed by B or the post published by node B is browsed by A, then A and B nodes form an undirected edge; The number is measured by the degree of the node.

The network construction algorithm is as follows^[12]

- Growth: Initially given n nodes, add a new node at each time step, and generate $m(m < n)$ new edges;
- Preferred: The probability that the new node j and the old node i will be connected to each other is:

$$\prod k_i = \frac{k_i}{\sum_j k_j} \tag{1}$$

BA scale-free network evolves through t steps, which can generate $N = n + t$ nodes and mt edges.

SPOC Face-to-Face Network

This paper will use the small world network as the underlying network. In order to avoid the WS small world network in the process of building isolated nodes and the results are biased, this paper will use the NW network proposed by Newman and Watts as the communication network under the SPOC. The nodes on the NW network represent learners. If the learners are members of the discussion group, a corresponding relationship (edge) is generated.

The network construction algorithm is as follows^[13]:

- Given a rule network: the total number of nodes of a given network is N , and each node is connected with its nearest neighbor $K = 2k$ nodes to obtain a one-dimensional limited rule network, requiring: $N \geq K \geq 1$;
- New random network: For the N nodes of the rule network, the probability of connecting any two nodes is $pK / 2$, but to keep the edge of the original rule network unchanged, it is also necessary to exclude the repeated connection and its own connected.

Knowledge Dissemination Mechanism

Based on Lin, Li^[14, 15] and other knowledge spillover diffusion perspectives, this paper considers the participation factors of neighbors and establishes a knowledge dissemination model.

Assuming that there are N nodes in the system and the number of them remains the same, the transfer of knowledge can only occur between the nodes and their neighbors and knowledge transfer must occur when there is a knowledge gap between the two individuals. At t moment, the knowledge of the node i can be represented by $v_i(t)$, and the knowledge update of the node i as follows:

$$\begin{cases} v_i(t+1) = v_i(t) + \alpha_i[v_j(t) - v_i(t)] & \text{if } v_j(t) > v_i(t) \\ v_i(t+1) = v_i(t) & \text{otherwise} \end{cases} \tag{2}$$

Extracting knowledge from the neighbor j of the node i with probability T :

α_i is the absorption capacity coefficient of individual i ; α_i is the random number online and meets inverted U-shaped distribution in $(0,1]$ offline; $v_i(t) \in [0,1]$, here $v_i(t) = 0$, $v_i(t) = 1$ means node i doesn't master the new knowledge and can grasp the complete new knowledge separately at t moment.

Considering the knowledge complexity $dk (dk \neq 0)$, the absorption capacity coefficient of individual i can be written as :

$$\alpha'_i = \alpha_i / dk \quad (3)$$

Considering the participation of neighbors, the probability of accepting knowledge transfer is

$$T' = T * T^{0.5-h(i)/k(i)} \quad (4)$$

rewritten as:

Where h represents the number of people participating in the discussion in the i -node neighbors, $k(i)$ is the degree of node i and α_i is the knowledge accept rate.

$$h = \frac{1}{N} \sum_i h(i) / k(i) \quad (5)$$

Define the overall participation of the network as:

At t moment, the average knowledge level and variance of the system are:

$$\bar{v}(t) = \frac{1}{N} \sum v_i(t) \quad (6)$$

$$\sigma^2(t) = \frac{1}{N} \sum v_i^2(t) - \bar{v}^2(t) \quad (7)$$

Double-Layer Network Knowledge Dissemination Process

From a certain moment, the individual receives new knowledge from the teacher. Due to the needs of the learning task, the face-to-face communication below the SPOC and the forum discussion on the MOOC begin.

According to Ferguson^[16], the learners on MOOC forums can be divided into two categories: (1) Silent learners: who can post but does not participate in the reply. (2) Contributors: who can participate in replies to other students' posts. Here, we take contributors as 40% of the total number of online users as the original parameter.

Online Forum Knowledge Flow

Learners on MOOC can post a message to seek the participation of others in the discussion of the content of the post, so as to obtain knowledge by the corresponding probability T'_1 to update their knowledge reserves, or learners to participate in the reply to make the poster knowledge can be obtained from its replies to the discussion with probability T'_1 . Considering that individuals will be more inclined to participate in the acquaintance's post discussion, this paper assumes that when the target node and the neighbor node on the MOOC are both SPOC offline users, $T'_1 = 1$

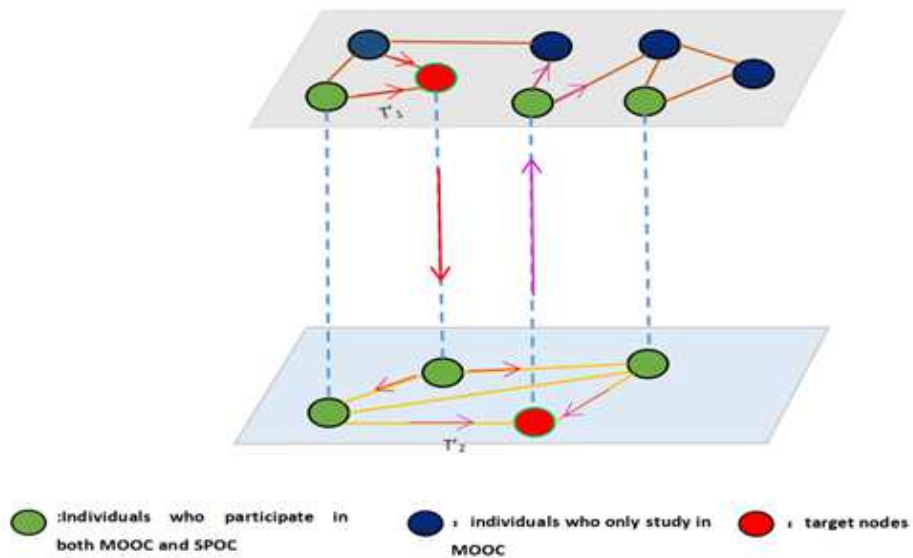


Figure 1: Schematic Diagram of the Spread of Knowledge in Double-Layer Network

Synchronizing the Information of the Connected Nodes

If the posting learner is also an individual who participates in the SPOC face-to-face discussion, at this time, the overall offline knowledge level is also increased because the node acquires knowledge online. The neighbors in SPOC have the opportunity T_2' to get more knowledge by discussing with this node. The two-layer network is connected by the connection node, and the knowledge between the two layers flows;

At the same time, the learners who are in SPOC face-to-face discussion update their knowledge level on the MOOC forum in real time. So that it has the opportunity to participate in the discussion of other individuals on the online forum, so that the knowledge between the two layers can flow to each other. Repeat this knowledge transfer process to form a dynamic two-tier knowledge transfer network.

Simulation Results and Analysis

In this paper, the original parameters are set as follows: $T=0.5$ 、 $dk=1.0$ 、the average absorption capacity offline is 0.6. And the original network parameters are shown in the Table1.

Table1: Parameters Settings of Initial Network

Max step	NW Network(Face-to-Face Discussion)			BA Network(Online Forum)		
	Size	Degree	Edge-Adding Probability	Size	Degree	Connection Number of New Nodes
200	100	6	0.25	4000	3	3

The Social Competence

SPOC face-to-face learners can form a "student-student" interactive communication group in self-organization, teaching rules, and other requirements. At this time, learners' social competence is embodied in the ability to actively and become learning partners with the members of the surrounding non-self-contained groups. In our model, we can use the

Edge-Adding probability of offline NW model to describe this kind of social competence. The stronger the social competence of offline individuals, the easier it is to establish learning partnerships with non-learning partners. Similarly, the greater the Edge-Adding probability in the model, the easier it is to succeed in edge-adding. Based on this hypothesis, we simulate the offline social competence of offline individuals by changing the Edge-Adding probability of offline networks, in order to explore the influence of offline social interaction on offline and online forum knowledge dissemination.

Learners' social competence is set as a parameter pt . The simulation results as follows:

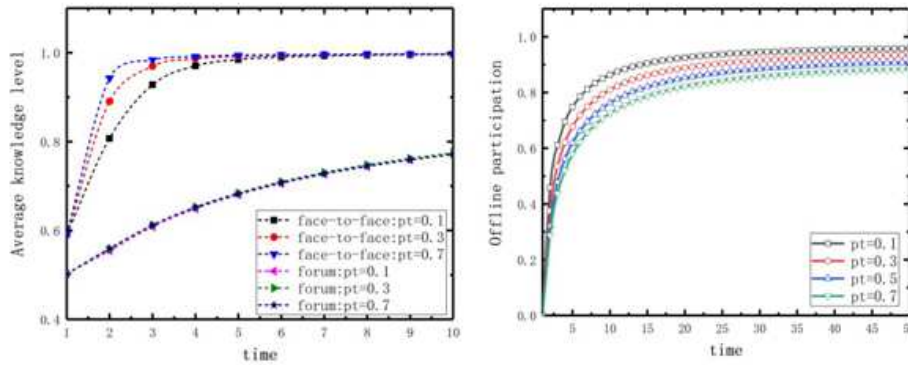


Figure 2: The Influence of Offline Individual Social Competence on the Knowledge Dissemination and Participation of Face-to-Face Communication

The left image of Figure 2 shows the evolution of the average level of knowledge on MOOC online forums and SPOC face-to-face communication with individuals with different social competencies over time. It can be seen that with the improvement of the social ability of individual’s offline, the amount of knowledge reserve will increase and the growth rate of knowledge will accelerate in unit time; however, the participation degree of offline network will decrease slightly with the improvement of the social ability of individuals offline. We believe that this is because with the improvement of the social ability of individuals, the number of neighbors (nodes) around individuals will increase. As the number of neighbors increases, it is not guaranteed that knowledge transfer will occur for each new learning partnership, which will lead to a smaller degree of neighborhood participation of some individuals.

We linearly fit the degree of participation and social competence of face-to-face communication. There is a linear relationship between the two, and the fitting formula is obtained.

$$h(pt) = 0.98004 - 0.10762 * pt \tag{8}$$

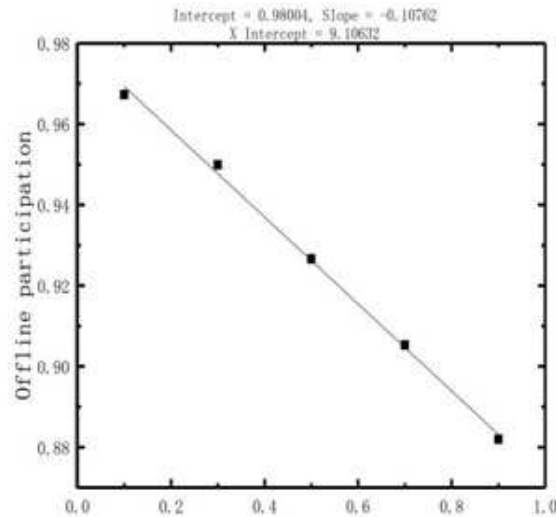


Figure 3: Fitting the Relationship between Offline Social Competence and Participation

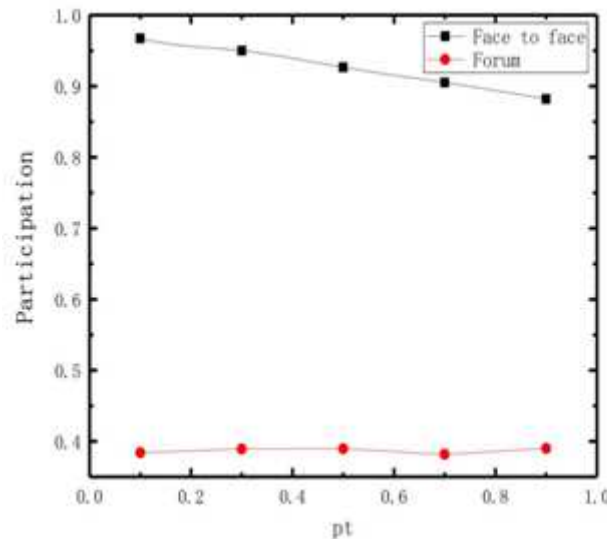


Figure 4: The Influence of Offline Social Competence on Online Participation

From Figure 2 (left chart) and Figure 4, we can see that the participation of online MOOC forums will change slightly with the change of offline social competence of offline individuals, but it is not as regular as the participation of offline face-to-face individuals with the change of social competence. Similarly, the change of average level of knowledge on MOOC does not show a significant change. Therefore, we believe that changing the social competence of offline individuals has a more significant impact on the knowledge dissemination and participation of face-to-face communication, and has no obvious effect on the knowledge dissemination and participation of online forums. This is because offline social competence changes will directly affect offline networks, offline networks can be directly and real-time affected by offline individual social competence changes. Online network is not directly affected by the change of individual social ability offline. After the increment of knowledge acquired offline, offline individuals update their knowledge level on online forums. In addition, the number of SPOC face-to-face individuals in online MOOC forums is relatively small. At this time, online forums are weakly affected by the social ability of offline individuals, and the social ability of offline individuals changes as a whole. There is no significant effect on the dissemination of knowledge and participation in online forums.

The Distribution of Absorptive Capacity

We divided the average level of knowledge absorption ability into three levels: low level (< 0.5), medium level (= 0.5), high level (> 0.5). In reality, the average absorptive capacity of the offline learning group will be low, medium (ordinary class) and high (elite class). What impact will different absorptive capacity have on the participation and knowledge dissemination of online forums and face-to-face exchanges?

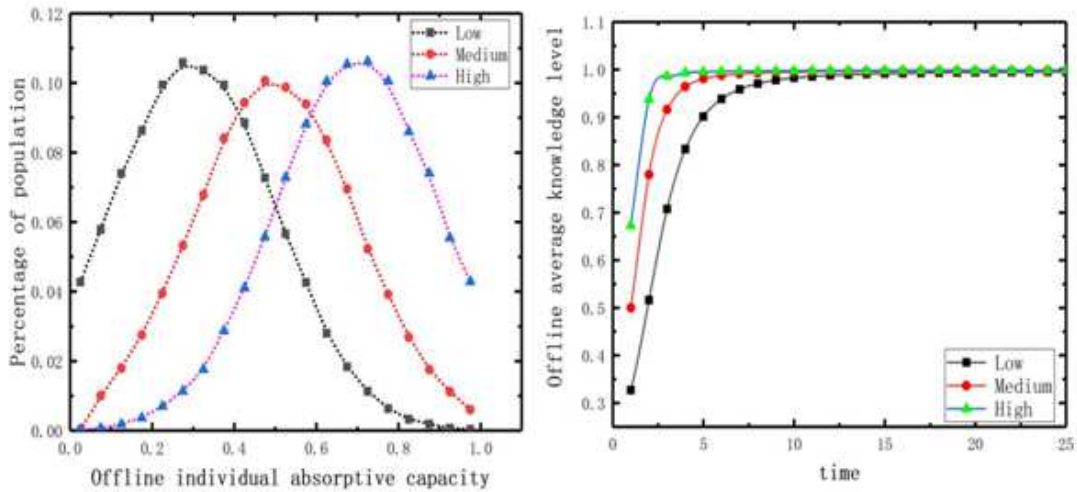


Figure 5: The evolution of Offline Knowledge Dissemination Over Time with Different Offline Absorption Capacity Distributions

Figure 5 left chart shows the distribution of offline individual's different absorptive capacity , and the right chart shows the evolution of the average level of knowledge exchanged . It can be found that the knowledge absorptive capacity of offline individuals presents an inverted U-shaped distribution; when the average offline absorptive capacity of the face-to-face group is stronger, the higher the overall knowledge level in the initial stage, the higher the offline growth rate of the average knowledge level, and the shorter the time for the "convergence" of the knowledge level among individuals. Undoubtedly, when the average offline absorptive capacity is low, there will be a lower efficiency of absorbing knowledge among individuals, which makes the increment of knowledge smaller in unit time, and makes the spread of knowledge slow. If the group has a higher average absorptive capacity, it means that most individuals have strong absorptive capacity, and these individuals can acquire more knowledge increment in unit time, so that the overall speed of knowledge dissemination is faster.

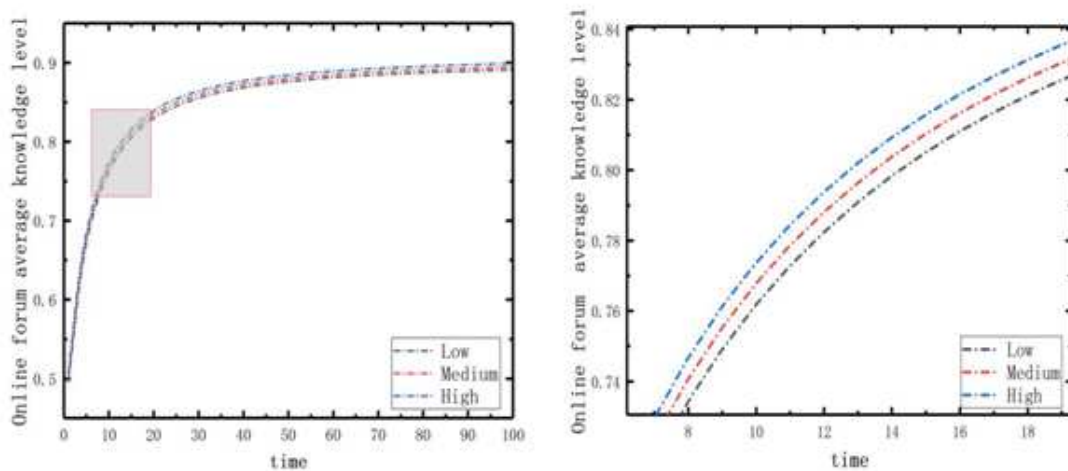


Figure 6: Change of Knowledge Dissemination in Online Forum Over Time with Different Offline Absorptive Ability

Figure 6 shows the evolution of the average knowledge level in forum over time under different offline absorptive capacities. We found that when the average offline absorptive capacity is higher, the average knowledge level of online forums will be higher in unit time. As offline individuals also participate in online forum learning interaction, when the average absorptive capacity of offline groups changes, it means that the absorptive capacity of some online individuals also changes accordingly. If the average absorptive ability of offline group is higher, there are some learners who come from offline face-to-face discussion with higher absorptive ability online. With the improvement of this part of users' absorptive ability, this part of users can absorb more knowledge increment in forum interaction. At the same time, because this part of users participates in the reply of other people's posts, other learners will get more knowledge increment from the responses of these learners. The higher the average absorptive capacity of offline groups, the higher the average online knowledge level will be. From the images, we also find that there is no significant difference in the average individual knowledge level of online forums with the change of the average absorptive capacity of offline groups, because the number of SPOC users is smaller than that of MOOC, in the face of large-scale MOOC learning groups, the absorptive ability of SPOC learners has limited impact on the overall average knowledge level of MOOC forums.

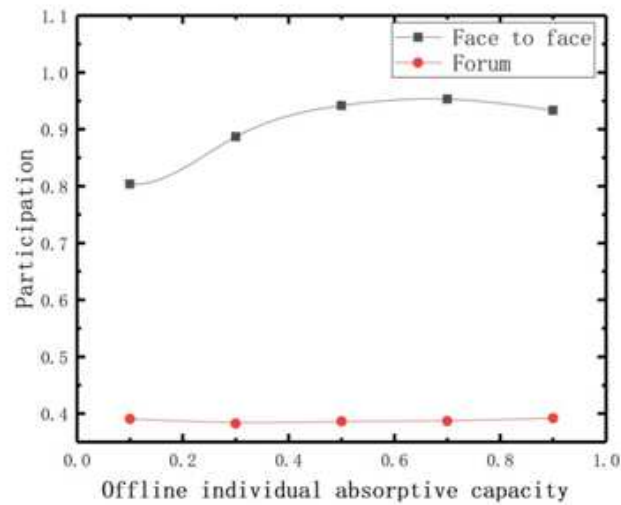


Figure 7: The Influence of Different Offline Average Absorptive Capacity on Online Forum, Face-to-Face Interaction Participation

The graph above shows the relationship between the total participation of online forum and offline face-to-face networks and the average absorptive capacity of offline groups when they reach the maximum time step set by the system. It can be seen that the participation of online forums is not affected by the change of the average absorptive capacity of offline groups, while for offline networks; the overall performance is that when the absorptive capacity is strong, the participation will be higher. For offline network, because the knowledge level of individuals is constantly updated in face-to-face communication, when the average absorptive capacity of the group is strong, the individual offline will get more knowledge level improvement, so that he can participate in face-to-face communication between members more smoothly. One of the factors affecting the online individual participation in the forum discussion is the difficulty of the poster's posts. However, the difficulty of the posts is not updated in real time with time. Once the knowledge level of the contributor is greater than the difficulty of the posts, he can participate in the discussion. At this time, if his absorptive ability improves, it will not affect his response to the posts. Therefore, as the average absorption level of the offline group increases, online participation remained basically unchanged.

In summary, the simulation results and analysis show that different distribution of offline absorptive capacity has a significant impact on the average level of knowledge and participation in the process of face-to-face communication. The stronger the average absorptive capacity of offline individuals, the more conducive to the growth of the overall level of knowledge.

The average knowledge level of online forums will be improved by the improvement of the average offline absorptive capacity, but the participation degree of online forums is hardly affected by the change of the average offline absorptive capacity.

The Knowledge Complexity and the Proportion of Contributors Online

The complexity of knowledge taught in different courses and classes is different. Will knowledge points of different complexity have an impact on knowledge dissemination online? Based on this model, the simulation results are as follows:

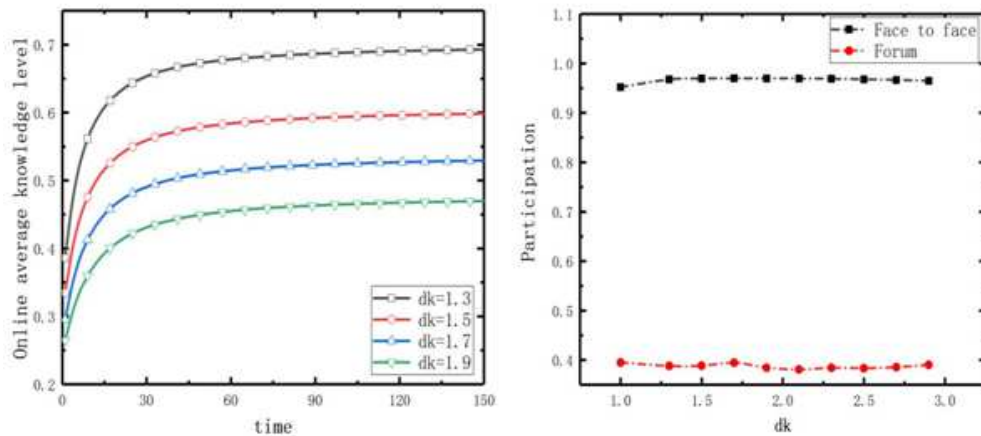


Figure 8: Effects of Different knowledge Complexities on Knowledge Dissemination and Participation in Online Forum

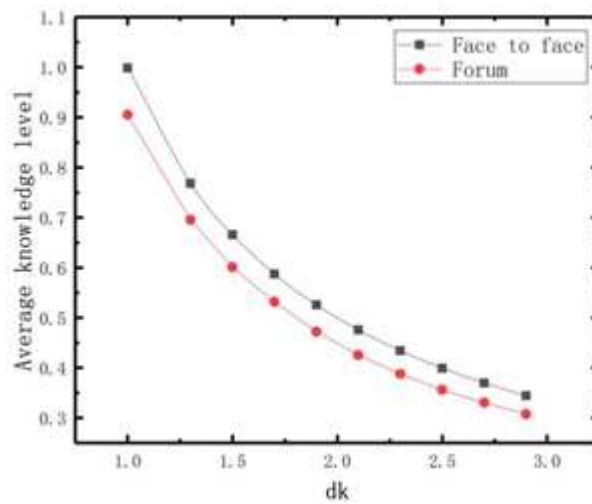


Figure 9: The Relation between Different Knowledge Complexity

As can be seen from Figure 8, with the increase of knowledge complexity, the speed of knowledge dissemination in online forums will slow down and the average level of knowledge will decrease. However, the impact on the participation of online forums is not too obvious. With the change of knowledge complexity, the participation of online forums will fluctuate and there is no obvious regularity. As the complexity of knowledge increases, according to formula (3), it can be seen that knowledge becomes more complex and the individual's ability to absorb knowledge decreases accordingly, which will hinder the transfer of knowledge among individuals, slow the transfer of knowledge and is not conducive to the dissemination of knowledge. The simulation results show that the average knowledge level of the network is inversely proportional to the complexity of knowledge at steady state, as shown in Figure 9 below.

According to the statistical results of Ferguson ^[16], we take contributors as *per*=15%, 20% and 30% of the total number of online users, respectively, to study the impact of the proportion of contributors on online knowledge dissemination and participation.

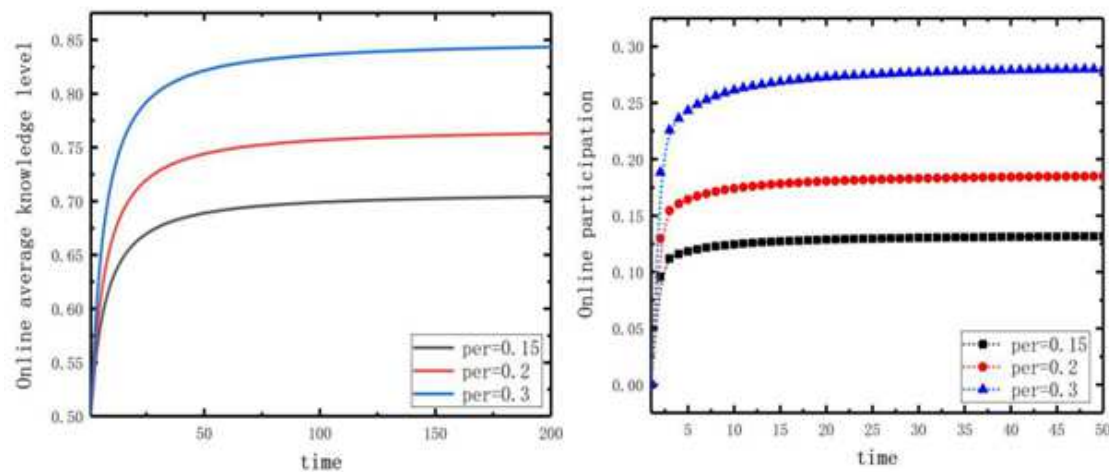


Figure 10: The Evolution of Average Knowledge Level and Participation Degree of Online Forum over Time with Different Contributors

Figure 10 shows the evolution of average knowledge level and participation over time for online forums with different contributors (per). From the simulation results, it can be found that when the contributors account for a relatively high proportion, the average knowledge level rises faster. When the maximum time step is reached, the overall level will reach a higher average knowledge level; as the proportion of contributor's increases, the overall participation of the forum will increase at a faster rate, and there will be a higher level of participation in the steady state. Since only the contributors will take the initiative to participate in the reply of other people's posts in the forum, when the proportion of contributors increases, the number of people in the group who can participate in the forum reply interaction will increase, which can improve the participation of the forum, and is conducive to the transfer and dissemination of knowledge. Therefore, the proportion of contributors in online groups will significantly affect the online knowledge dissemination and participation.

CONCLUSIONS

Based on the viewpoint of knowledge spillover, considering the participation of neighbors and the complexity of knowledge, this paper proposes a two-layer network model to explore how offline individual activities or organizations affect the participation degree and knowledge dissemination of online MOOC forums in the face-to-face learning process of offline SPOC. Through Monte Carlo simulation, this model explores the influence of offline individual's social competence, different distribution of offline individual's absorptive capacity, knowledge complexity and the proportion of online contributors on the knowledge dissemination and participation of online forums. It is concluded that: (1) the proportion of online contributors will affect the participation and knowledge dissemination of online MOOC forums to a large extent; (2) different distribution of offline absorptive capacity will affect the average knowledge level of online forums to a certain extent; (3) the more complex the knowledge is, the less conducive to the dissemination of online knowledge; (4) offline social ability, different levels of offline absorptive capacity and knowledge difficulty have little impact on the participation of online forums.

Of course, this model is a relatively preliminary qualitative inquiry model. In order to simplify the research process, many factors have not been considered, such as: this paper only studies single knowledge dissemination, real

MOOC learning network is not a strict BA network, establishing a directed network to study online forum response discussion will be more appropriate, not empirical, and so on. These issues need to be considered and they will also be a problem we will try to solve in the future.

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