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The Evolving Patterns of Collective Attention among Lurkers in a cMOOC

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Abstract: Lurkers, learners with low engagement, constitute a significant portion of online learning environments. Understanding the learning patterns of lurkers is crucial for the advancement of online education. While existing research has extensively explored the phenomenon and causes of lurking behavior, few studies have deeply analyzed the specific learning processes of lurkers. This study investigates the collective attention flow evolution of two types of lurkers – “experienced lurkers” and “inexperienced lurkers” – within a connectivist massive open online course. Our findings reveal that both groups exhibit similar logarithmic growth curves in their collective attention flow, indicating a participation pattern characterized by a rapid initial increase, followed by a deceleration, and eventual stabilization. Furthermore, the collective attention flow network of *inexperienced lurkers* demonstrates a centralized structure, suggesting that a subset of resources dominates their attention allocation.

Keywords: Lurkers, cMOOCs, collective attention, evolving pattern

1. Introduction

Connectivist Massive Open Online Courses (cMOOCs) hold the potential to foster interconnected learning networks and leverage collective intelligence. By facilitating connection, resources sharing, and knowledge co-creation among learners, cMOOCs promise to democratize education and address complex problems collaboratively. However, a significant challenge lies in the prevalence of lurkers, learners who primarily observe without actively contributing (Bozkurt et al., 2020). This inhibits the realization of full potential of cMOOCs.

The concept of collective attention offers a promising approach, particularly when coupled with clickstream data analysis. Collective attention refers to the shared focus of a group on specific information resources (Wu & Huberman, 2007), shaping online behavior and influencing knowledge dissemination. By analyzing the flows of collective attention – the patterns of attention allocation within a group – as reflected in clickstream data, insights can be gained into how lurkers interact with course materials, what attracts their interest, and how these attention patterns evolve over time. This is especially relevant in cMOOCs, where a vast amount of information is generated and shared dynamically. This study aims to leverage clickstream data to characterize the attention flows of lurkers and uncover the evolving patterns of their engagement.

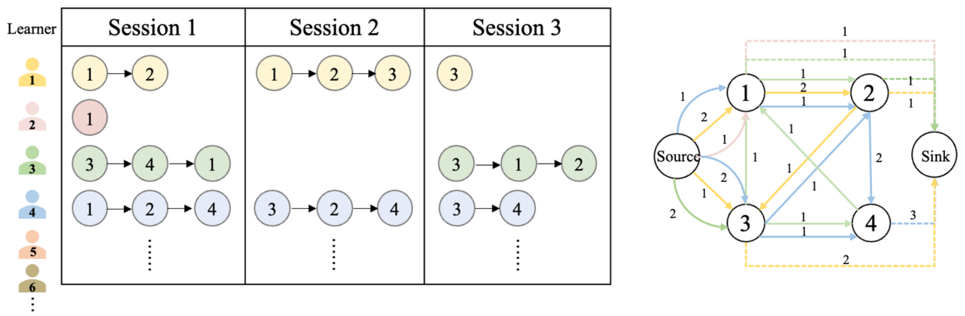
2. Method

2.1 Contexts

This study examines lurkers behavior within the fifth iteration of the cMOOC "Internet plus Education: Dialogue between Theory and Practice," developed by Beijing Normal University. The 12-week course, involving 721 participants from diverse backgrounds, focuses on the collaborative construction and sharing of learning resources. Of these participants, 559 (77.53%) were identified as lurkers (i.e., those who never post any contents), with 129 having prior experience in the course ("experienced lurkers") and 430 being new to the course ("inexperienced lurkers"). This study aims to model and compare the evolving patterns of collective attention flows within these two groups to understand the influence of prior learning experience on engagement in connectivist online learning environments.

2.2 Collective Attention Flow Network Construction

Learning logs were automatically collected by the learning platform during the course. After preprocessing, a total of 4,623 clickstream data points from lurkers were obtained. Based on the open flow network model, collective attention flow networks were constructed for both the "experienced lurkers" and "inexperienced lurkers" learning groups. As illustrated in Figure 1, learner clickstream data was segmented into distinct sessions based on learning time, and then aggregated at the group level. In this model, nodes represent specific learning resources, and directed edges represent the direction and frequency of attention flow between resources. Furthermore, "Source" and "Sink" nodes represent the external environment, balancing the flow of attention between online and offline spaces. The directed edge from "Source" to a resource represents the initial flow upon entering the online learning space, the directed edge from a resource to "Sink" represents the attention flow from that resource to the offline space.



(a) Clickstream data (b) Open flow network of collective attention

Figure 1. Collective attention flow network construction.

To explore the evolution of collective attention flow, we constructed and compared collective attention flow networks for both groups across weekly intervals. Analysis focused on network size (number of nodes and edges) and network structure (assessed via the power-law relationship ($C_i \propto T_i^{\eta}$) (Zhang & Wu et al., 2013). T_i is the total attention flow of node i and C_i is the influence of node i on network flow. A power exponent $\eta > 1$ indicates a centralized network structure, suggesting that certain nodes have a significant impact on attention flow, while $\eta < 1$ indicates a decentralized structure.

The collective attention flow network can be represented by the attention flow matrix $\boldsymbol{F}$, of size $(N+2) \times (N+2)$, where N is the number of learning resources and the total number of nodes is $N+2$ (including two special nodes). The elements of the matrix are denoted as f_{ij}. Thus, $T_i = \sum_{j=0}^{N} f_{ji} = \sum_{j=1}^{N+1} f_{ij}$, the sum of attention flow entering node i from the "Source" node (node 0) and other nodes within the network, or equivalently, as the sum of attention flow exiting node i to other nodes within the network and the "Sink" node (node $N+1$).

Node influence (C_i) reflects the overall attraction and influence of node i within the attention flow network. It quantifies the total amount of attention that directly or indirectly passes through node i, $C_i = \sum_{k=1}^{N} \sum_{j=1}^{N} (f_{0j} u_{ji} / u_{ii}) u_{ik}$, where u_{ij} is the element in the i-th row and j-th column of the fundamental matrix $\boldsymbol{U}$. $\boldsymbol{U}$ is defined as $\boldsymbol{U} = \boldsymbol{I} + \boldsymbol{M} + \boldsymbol{M}^2 + \cdots = (\boldsymbol{I} - \boldsymbol{M})^{-1}$, where $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{M}$ is the Markov matrix used to calculate the probability of attention flowing between nodes.

3. Preliminary Findings

As shown in Figure 2, the scope of attention flow expanded for both lurker types throughout the course. The network scale, in terms of both nodes and edges, exhibited similar logarithmic growth curves across both groups, characterized by three phases: rapid growth (Week 1-3), continued growth (Week 4-7), markedly reduced growth with gradual stabilization of network nodes and edges (Week 8-12). Owing to the difference in group size, the “inexperienced lurkers” (430 individuals) demonstrated a larger network scale compared to the “experienced lurkers” (129 individuals). This disparity in network scale increased progressively as the course unfolded. Furthermore, a minor increase in nodes and edges was observed in the “inexperienced lurkers” network during Week 7, potentially attributable to the specific learning topic of that week. This increase was not apparent in the network scale of “experienced lurkers.”

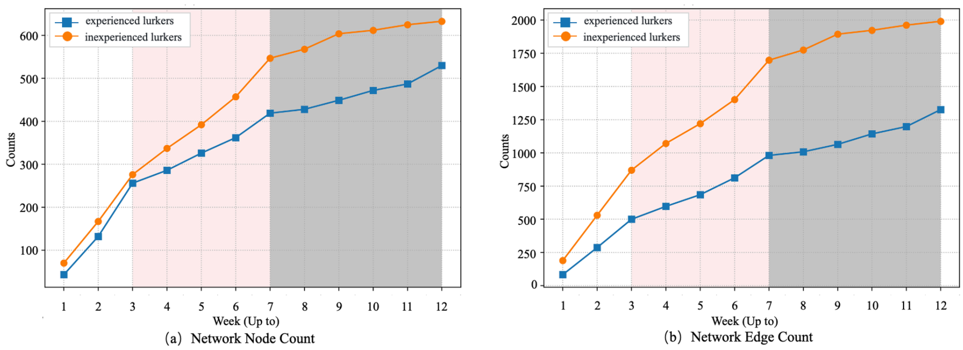


Figure 2. Evolution of collective attention flow network scale.

The results of network structure were shown in Figure 3, which shows a good fitness (as depicted in Figure 3.b). It reveals that the η value for the “experienced lurkers” network remained consistently below 1 throughout the course, while the η value for the “inexperienced lurkers” network remained consistently above 1. This suggests that the “experienced lurkers” formed a decentralized collective attention flow network, characterized by a lack *of* dominance *of* any single learning resource over attention flow. In contrast, the “inexperienced lurkers” formed a centralized network structure, indicating a greater influence of certain resources on their attention flow.

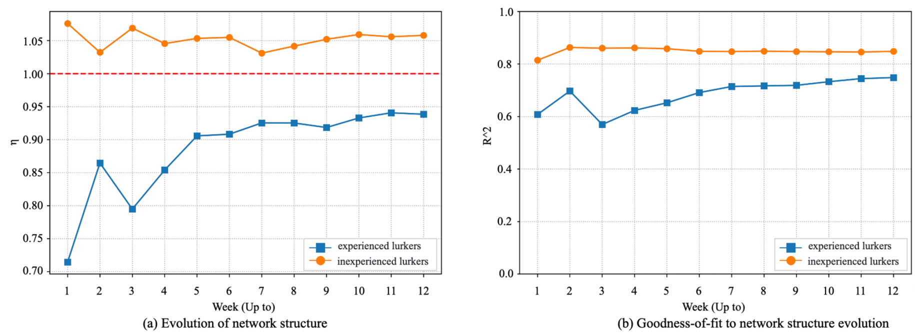


Figure 3. Evolution of collective attention flow network structure.

Acknowledgements

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