More Details about Experiments and Datasets

1 Datasets

The KuaiLive dataset used in experiments is available in our anonymous repository. Both KuaiLive and commercial datasets were sampled by selecting the top 10,000 active users and filtering out low-frequency rooms, as done in common GNN-based methods [35, 38]. We have provided additional statistical details of the commercial dataset, which reflect the characteristics of streaming, as illustrated in Table 1 and Fig. 1.

Table 1. Statistical details of commercial dataset. The terms #Avg-U, #Avg-R, and #Avg-S represent the average occurrence frequencies of users, rooms, and streamers, respectively. #Avg-SR denotes the average number of live rooms initiated by a streamer.

#Avg-U	#Avg-R	#Avg-S	#Avg-SR
51.0202	580.2494	202.0533	2.87

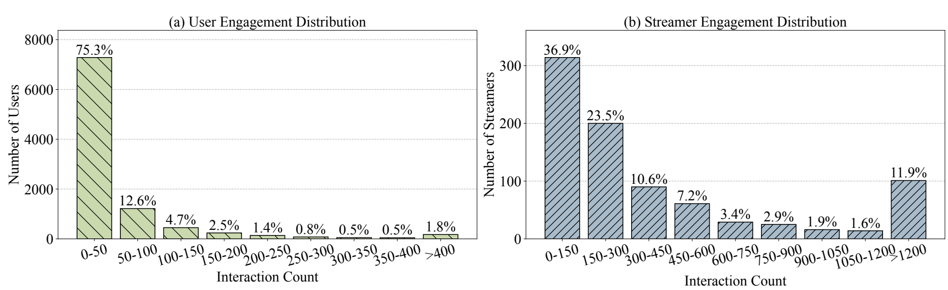

Fig. 1. Engagement distribution of users and streamers in the commercial dataset.

2 Experiments on Different U-S Density

To assess the robustness of DCGLive, we conducted experiments on U-S/U-R density discrepancies by modifying the LiveRec dataset [25] at various U-S densities. The original LiveRec dataset lacks U-S interaction information; therefore, we generated datasets with different U-S densities by adjusting the sampling rates. The datasets used for the experiment comprised 10,647 users, 804 streamers, and 8,185 rooms.

The performance of DCGLive on these datasets is shown in Table 2. The results indicate that DCGLive performs consistently across different density settings and achieves better outcomes at higher U-S densities, thereby validating the effectiveness of DCGLive. Additionally, the substantial U-R/U-S density discrepancies naturally occurring in our two real-world datasets further corroborate the effectiveness of DCGLive.

3 Case Study

During the evaluation phase, we conducted a visualization analysis of the evolving user and room embeddings within the KuaiLive dataset.

Specifically, we applied both t-SNE and PCA dimensionality reduction techniques to project the embeddings onto a two-dimensional plane. For the user embeddings, we selected the top-10 users

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Table 2. Performance of DCGLive on LiveRec across various density settings.

U-R Density	U-S Density	NDCG@5	NDCG@10	Recall@5	Recall@10	MRR
0.4391%	0.0112%	0.0287	0.0398	0.0449	0.0795	0.0409
0.4391%	0.0224%	0.0407	0.0565	0.0659	0.1152	0.0516
0.4391%	0.0448%	0.0409	0.0575	0.0654	0.1171	0.0568

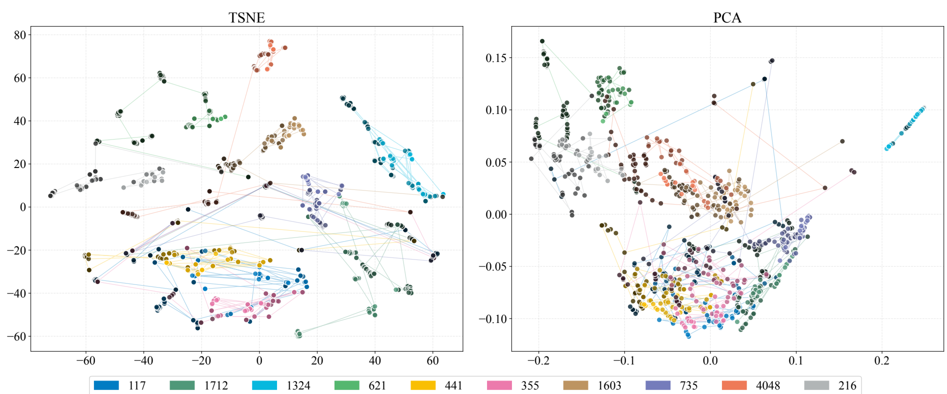

Fig. 2. Visualizing the trajectories of user embeddings over time.

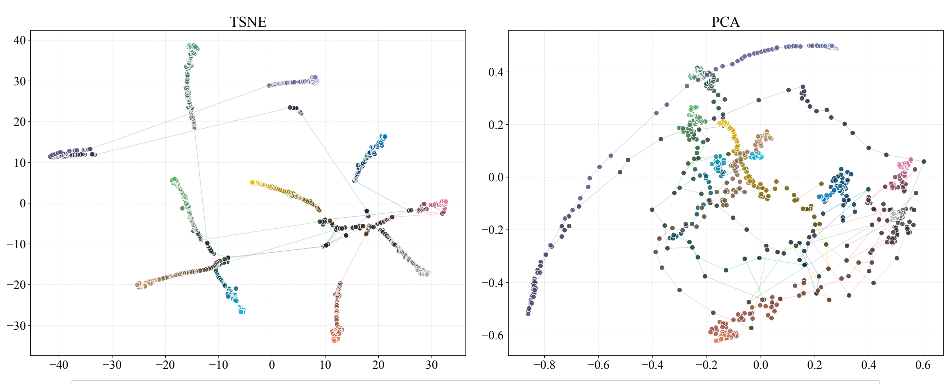

Fig. 3. Visualizing the trajectories of room embeddings over time.

based on the frequency of embedding updates during the test phase. For the room embeddings, we used a random sample of 10 rooms. The results are presented in Fig. 2 and Fig. 3, where the color gradient from light to dark represents the progression of time.

As observed in the figures, our proposed method effectively captures the evolving embeddings of both users and rooms, thereby enabling the characterization of their dynamic features. Specifically, a noticeable displacement in the embeddings of certain users and rooms between the early and late stages suggests significant shifts in their respective interests or topics over time. This observation supports the hypothesis that the effectiveness of our method is attributable to its fine-grained modeling of dynamics.

Furthermore, we analyzed the embeddings of different users, categorized by their respective LiveCI values (*LR*), as shown in Fig. 4. The figure clearly illustrates that users with high LiveCI values tend to cluster together, forming a distinct group, whereas users possessing lower LiveCI values are dispersed into several smaller, independent clusters. This experimental result provides empirical validation for the effectiveness of our proposed LiveCI metric.

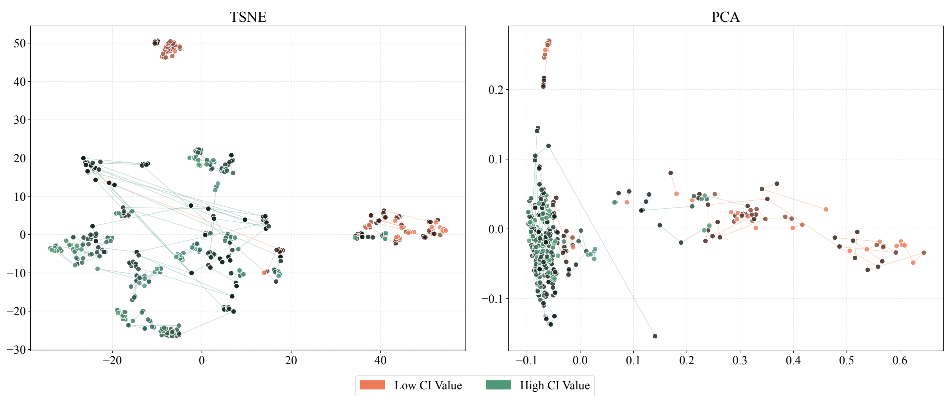

Fig. 4. Visualizing the trajectories of user embeddings with different LiveCI values.