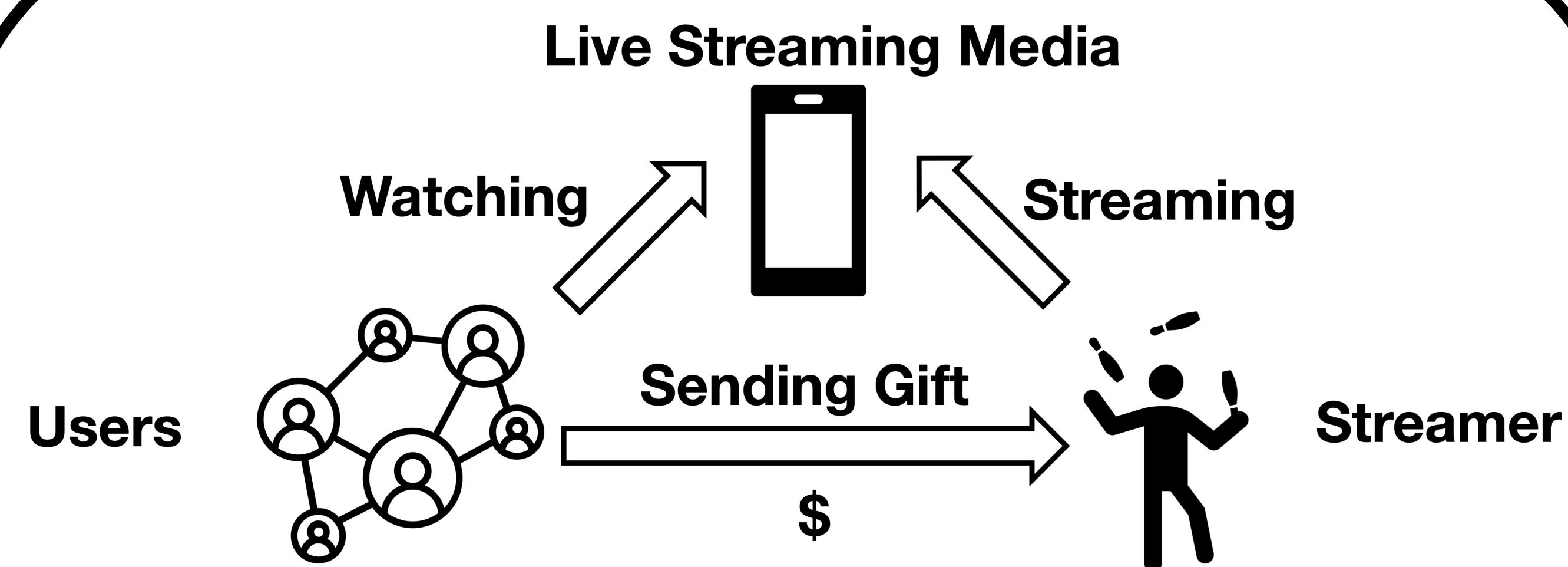


Introduction



The Live Streaming Gifting Scenario

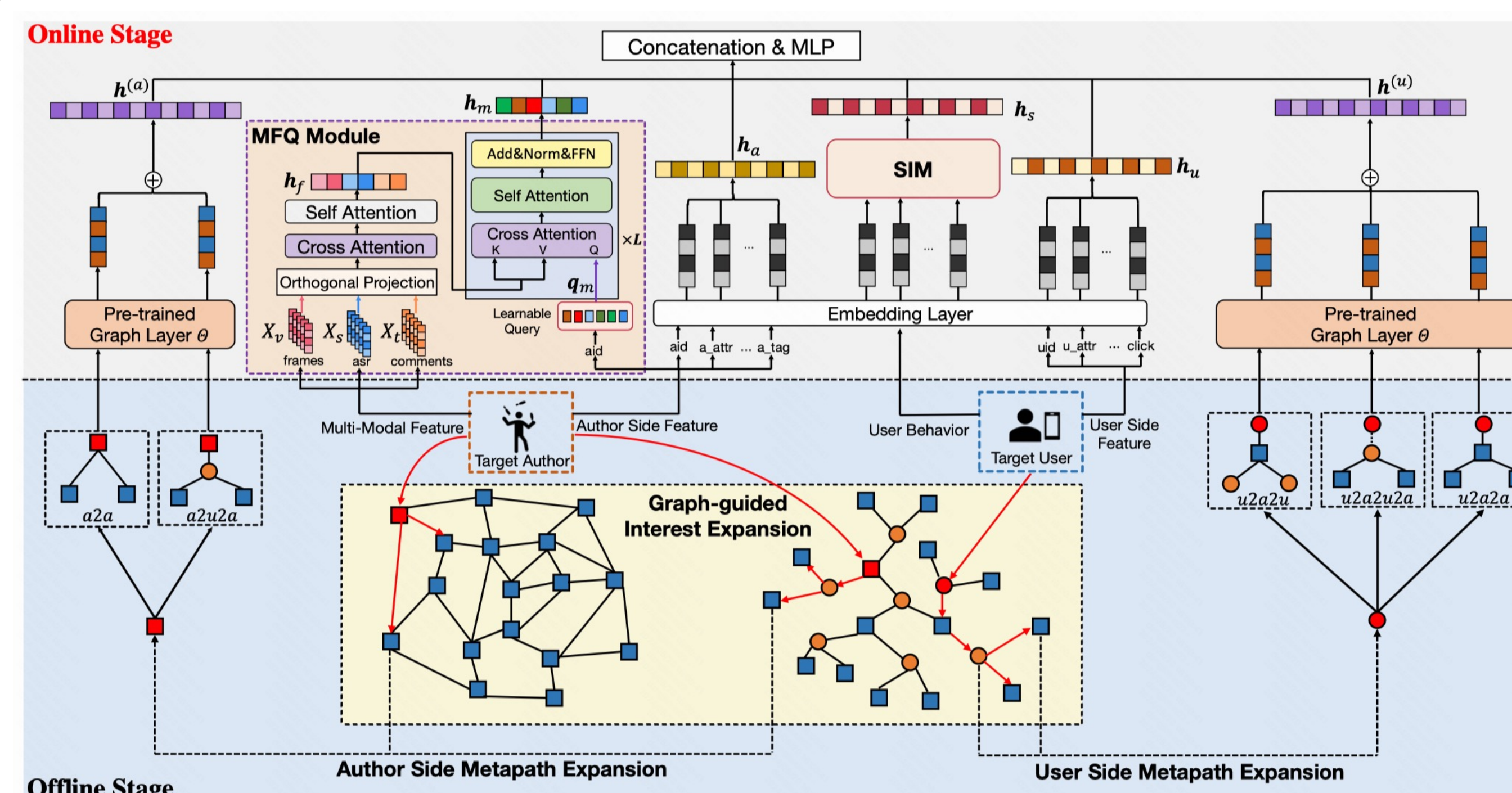
Motivation

- Different from conventional recommendation problem, it is challenging to precisely describe the **real-time content changes** in live streaming recommendation.
- Due to the **sparsity of gifting behaviors**, capturing the preferences and intentions of users is quite difficult.

Contributions

- The proposed Multi-modal Fusion with Learnable Query (MFQ) module leverages the dynamic multimodal content of live streaming and captures the distinct characteristics among streamers.
- Graph-guided Interest Expansion (GIE) module largely enriches the observed history behaviors of users and streamers with both self-supervised graph representation learning and metapath-based behavior expansion to alleviate the sparsity problem.
- Online A/B tests further show that MMBee brings significant online benefits and we build efficient industrial infrastructure to deploy MMBee on the real-world online live streaming recommendation.

Method



Multi-modal Fusion with Learnable Query

The proposed Multi-modal Fusion Module with Learnable Query (MFQ) module helps the model to perceive the real-time content changes in live streaming through processing the complex visual frames, comments and audio in each streaming segment.

$$h_v = \text{CrossAttention}(X_v W_v^Q, Y_v W_v^K, Y_v W_v^V), Y_v = \text{OP}(X_v, X_s, X_t)$$

$$h_s = \text{CrossAttention}(X_s W_s^Q, Y_s W_s^K, Y_s W_s^V), Y_s = \text{OP}(X_s, X_t, X_v)$$

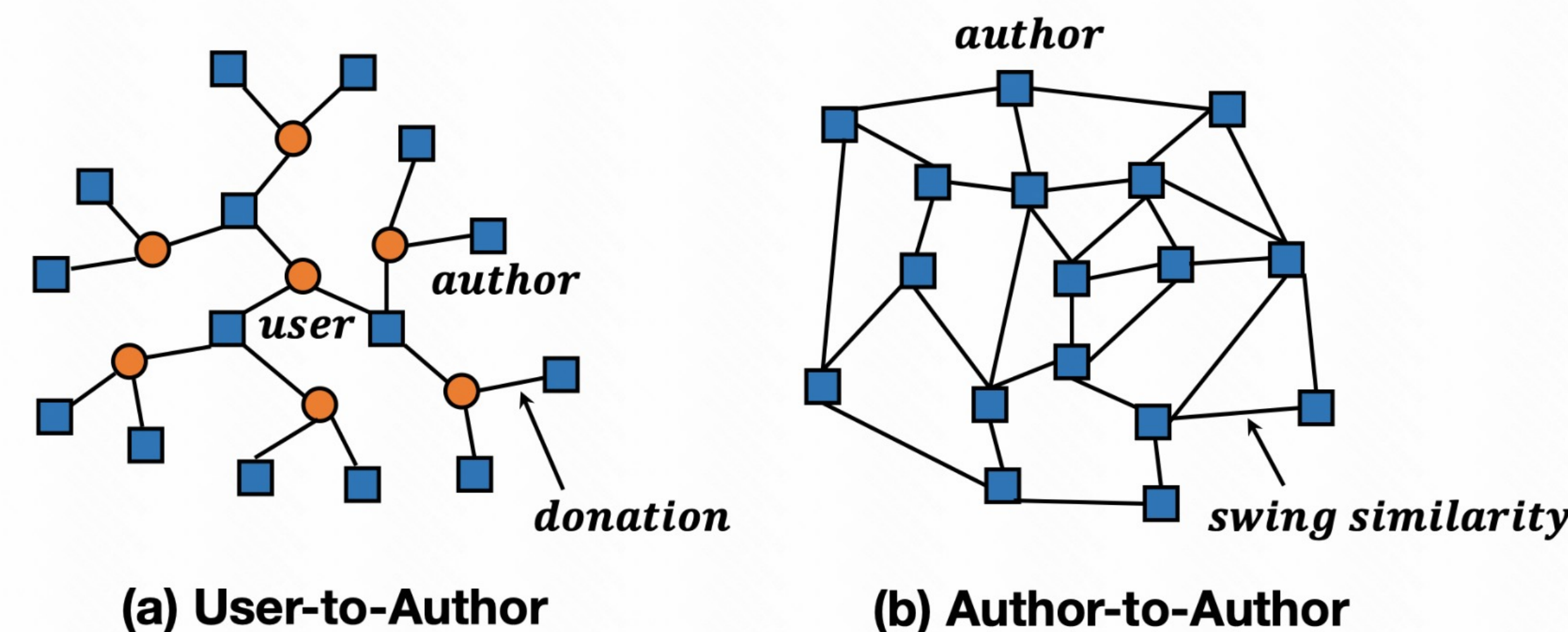
$$h_t = \text{CrossAttention}(X_t W_t^Q, Y_t W_t^K, Y_t W_t^V), Y_t = \text{OP}(X_t, X_s, X_v)$$

$$h'_m = \text{CrossAttention}(q_m W_c^Q, h_f W_c^K, h_f W_c^V)$$

Graph-guided Interest Expansion

$$\mathbb{E}^{(u)} = \{\Theta(v_i) | v_i \in \mathcal{N}_{\rho_{u2a2u}}^{(2)}(u_t) \cup \mathcal{N}_{\rho_{u2a2u2a}}^{(3)}(u_t) \cup \mathcal{N}_{\rho_{u2a2a}}^{(2)}(u_t)\}$$

$$\mathbb{E}^{(a)} = \{\Theta(v_i) | v_i \in \mathcal{N}_{\rho_{a2a}}^{(1)}(a_t) \cup \mathcal{N}_{\rho_{a2u2a}}^{(2)}(a_t)\}$$



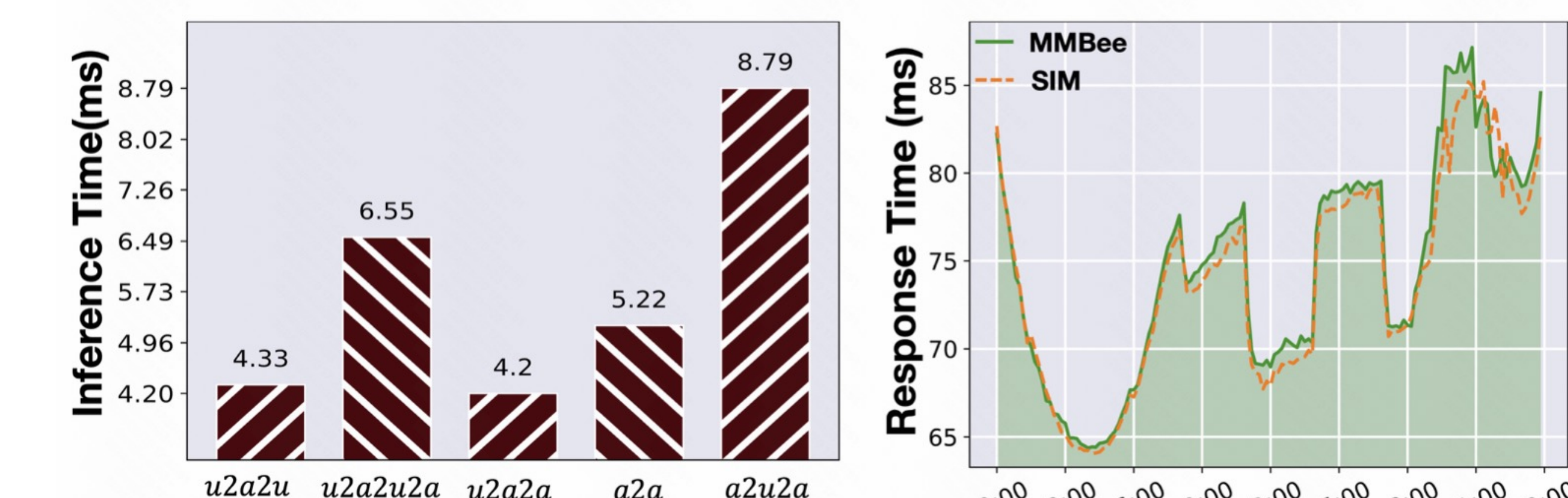
Experiments

Methods	GTR					
	AUC	Impr.*	UAUC	Impr.*	GAUC	Impr.*
MMoE [16]	0.956230	-	0.730186	-	0.746711	-
MMoE+BDR [39]	0.956908	+0.0678 %	0.730625	+0.0439 %	0.747136	+0.0425 %
MMoE+MTA [32]	0.957095	+0.0865 %	0.731450	+0.1264 %	0.747327	+0.0616 %
MMoE+EgoFusion [4]	0.956952	+0.0722 %	0.731418	+0.1232 %	0.747275	+0.0564 %
MMoE+MFQ	0.956902	+0.0672 %	0.731975	+0.1789 %	0.747275	+0.1764 %
MMoE+GIE	0.957064	+0.0834 %	0.733853	+0.3667 %	0.751239	+0.4528 %
MMoE+Ours(MFQ+GIE)	0.95723	+0.1001 %	0.735776	+0.5590 %	0.753017	+0.6306 %
SIM [20]	0.958656	-	0.732239	-	0.748383	-
SIM+BDR [39]	0.958419	-0.0237 %	0.734757	+0.2518 %	0.750684	+0.2301 %
SIM+MTA [32]	0.958867	+0.0211 %	0.734921	+0.2682 %	0.750802	+0.2419 %
SIM+EgoFusion [4]	0.959387	+0.0085 %	0.735608	+0.3369 %	0.751669	+0.3286 %
SIM+MFQ	0.959202	+0.0546 %	0.735717	+0.3478 %	0.751780	+0.3397 %
SIM+GIE	0.959802	+0.1146 %	0.738309	+0.6070 %	0.755154	+0.6771 %
SIM+Ours(MFQ+GIE)	0.960302	+0.1646 %	0.743678	+1.1439 %	0.76044	+1.2057 %
<i>p-value</i>		$1.02e^{-3}$		$2.01e^{-3}$		$5.12e^{-3}$

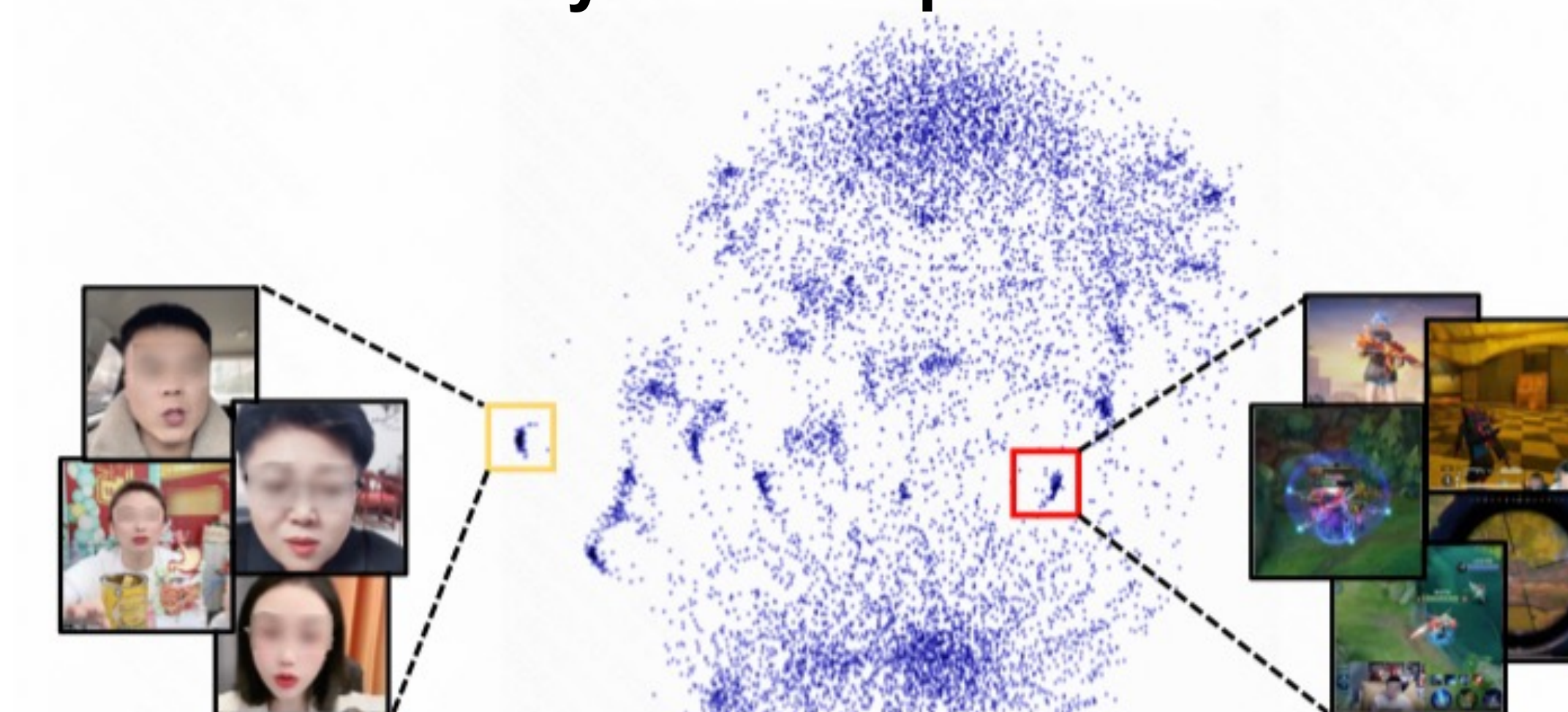
Performance on Kuaishou Dataset.

Methods	TikTok			Movielens		
	Recall@10	Precision@10	NDCG@10	Recall@10	Precision@10	NDCG@10
NGCF [28]	0.0292	0.0045	0.0156	0.1198	0.0289	0.0750
LightGCN [8]	0.0448	0.0082	0.0261	0.1992	0.0479	0.1324
MMGCN [30]	0.0544	0.0089	0.0297	0.2028	0.0506	0.1361
GRCN [29]	0.0392	0.0065	0.0221	0.1402	0.0338	0.0882
EgoGCN [4]	0.0569	0.0093	0.0330	0.2155	0.0524	0.1444
DIN [42]	0.0403	0.0074	0.0235	0.1372	0.0330	0.0912
SASRec [9]	0.0435	0.0043	0.0215	0.1914	0.0191	0.1006
SIM [20]	0.0413	0.0079	0.0245	0.1470	0.0429	0.1011
MMMLP [15]	0.0509	0.0081	0.0297	0.1842	0.0484	0.1328
MMSSL [20]	0.0553	0.0055	0.0299	0.2482	0.0170	0.1113
Ours	0.0605	0.0097	0.0347	0.2317	0.0566	0.1573
<i>p-value</i>	$1.29e^{-5}$	$6.23e^{-6}$	$7.29e^{-5}$	$2.75e^{-5}$	$2.81e^{-3}$	$1.61e^{-2}$

Performance on TikTok and ML Dataset.



System Response Time



Visualization Study