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GIFT: Graph-guided Feature Transfer for Cold-Start Video Click-Through Rate Prediction

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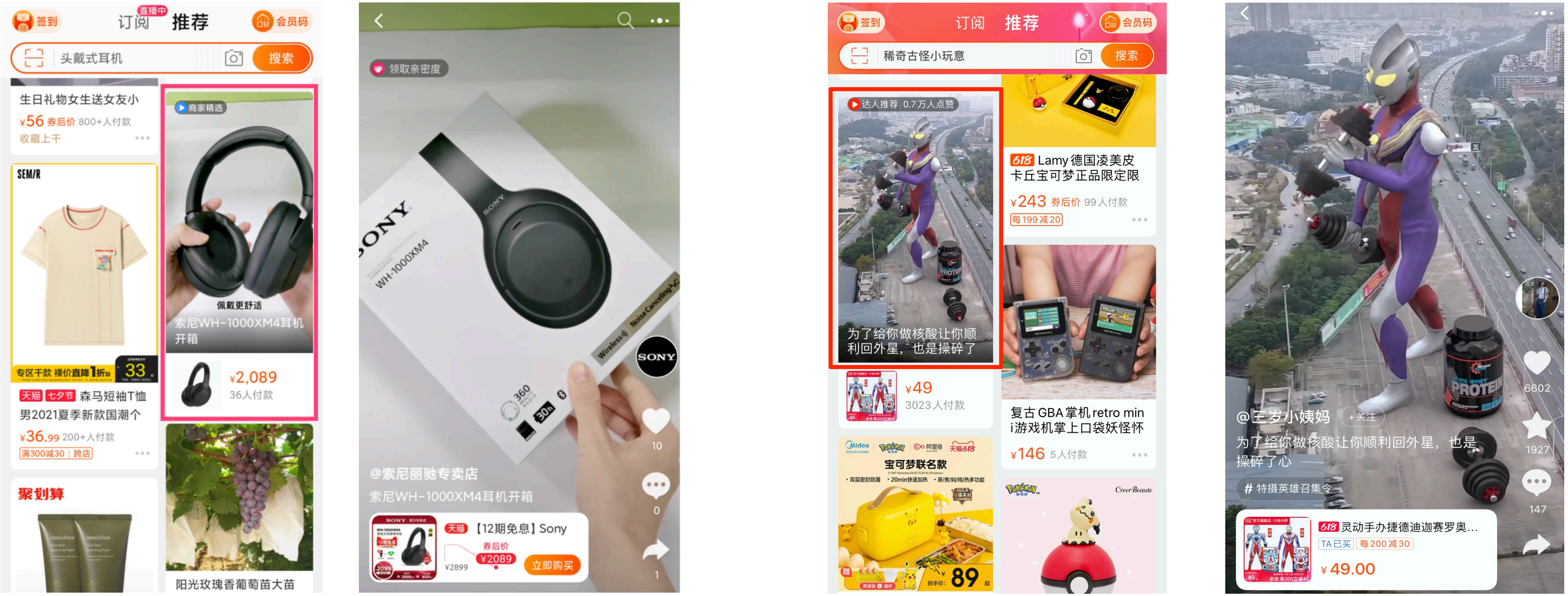
Background

- Short videos have witnessed rapid development in Taobao.
- To ensure the freshness of the content, platforms need to release a large number of new videos every day.



Short videos in the homepage feeds of Taobao App

Item-side cold-start recommendation

Cold-start problem:

1. Lack of historical interactions
2. Domain bias between cold-start and warmed-up videos

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Challenge:

1. Unmeaningful id representation & statistical features
2. Model focuses more on warmed-up videos (90%)

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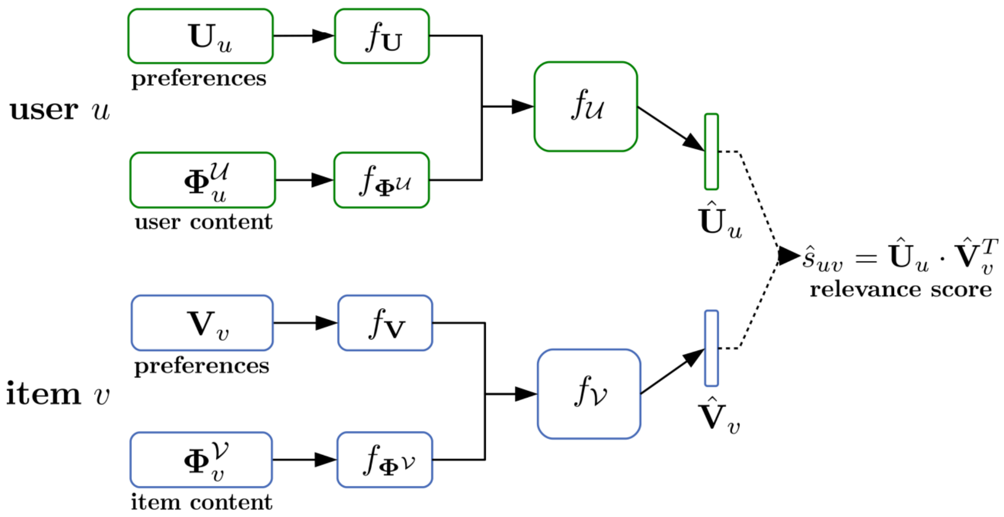
Current efforts in industry:

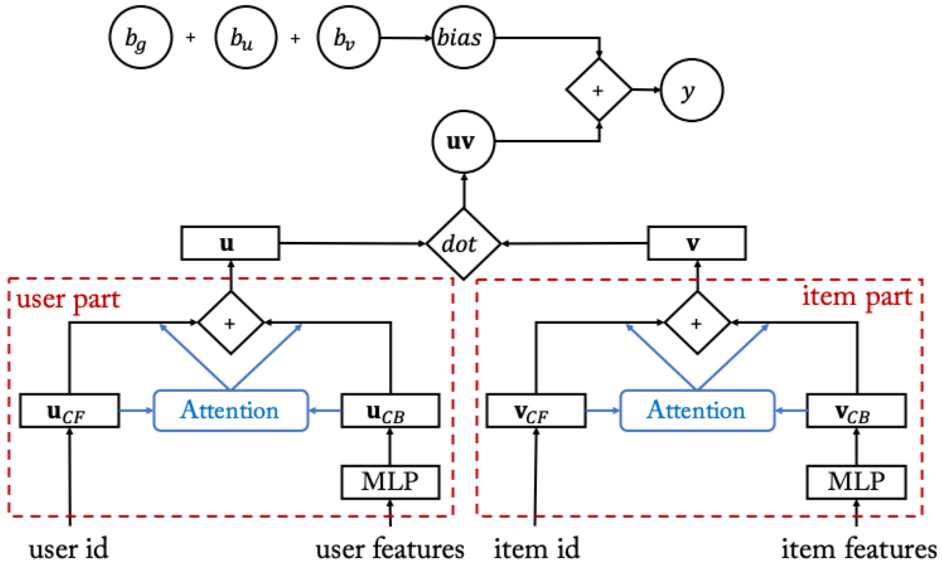
Add more side information to compensate for the id representation and statistical features (category, text caption, image, and video content representation, etc.)

Item-side cold-start recommendation

Domain-adaptation methods for cold-start recommendation



DropOutNet



ACCM net

Use dropout to make the model generalize to the missing features similar as cold-start items.

Attentively integrates id and content features to make model adapt to both warm and cold items.

Volkovs, Maksims, Guangwei Yu, and Tomi Poutanen. "Dropoutnet: Addressing cold start in recommender systems." Advances in neural information processing systems 30 (2017).

Shi, Shaoyun, et al. "Attention-based adaptive model to unify warm and cold starts recommendation." Proceedings of the 27th ACM international conference on information and knowledge management. 2018.

Graph-guIded Feature Transfer (GIFT) System

Construct linkages to guide feature transfer from warmed-up videos to cold-start ones

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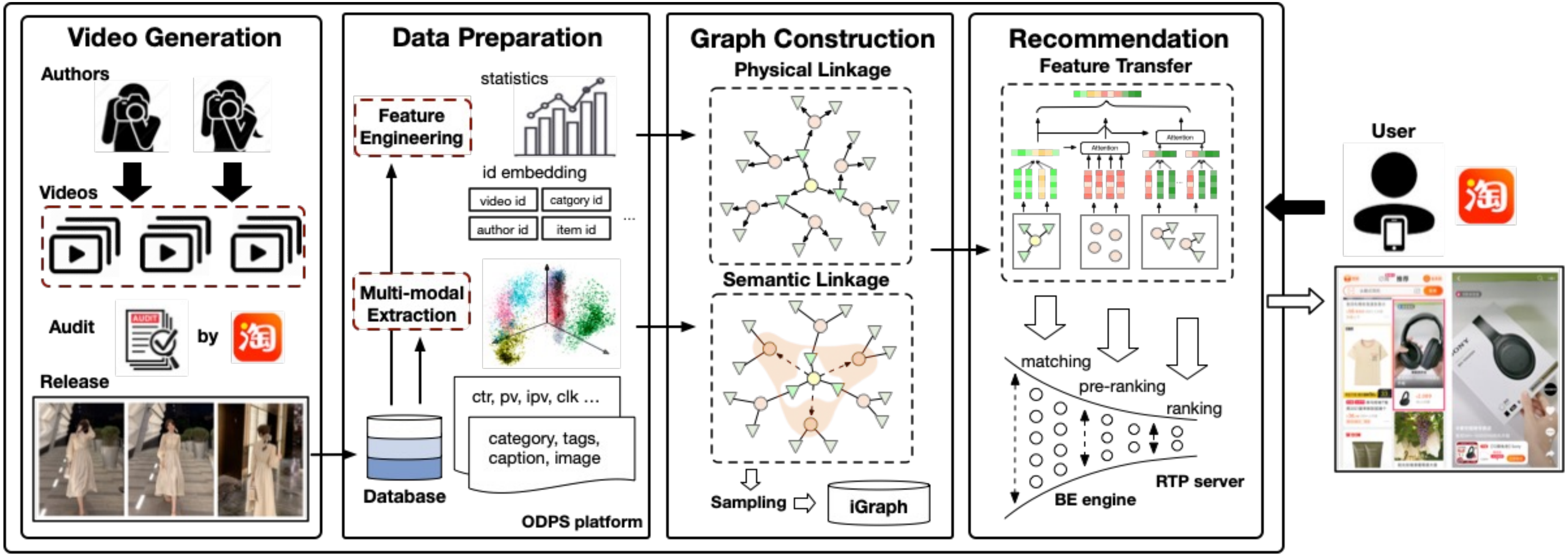

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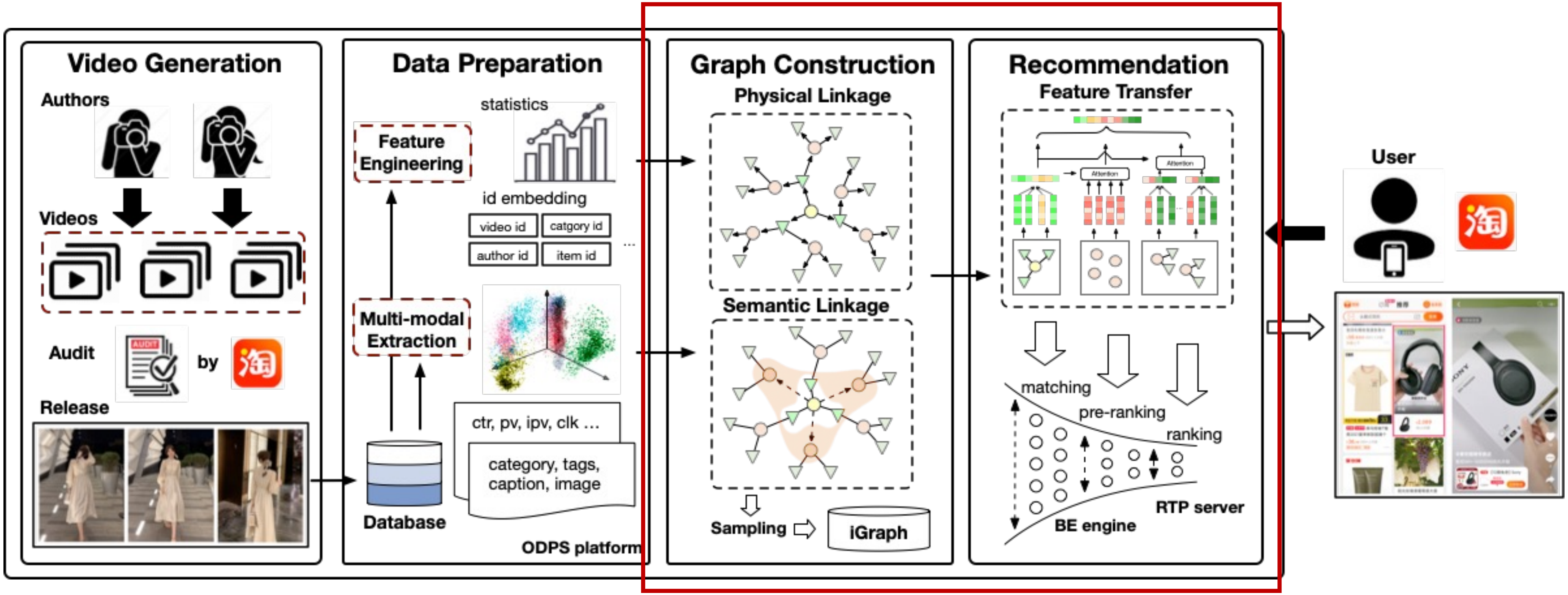
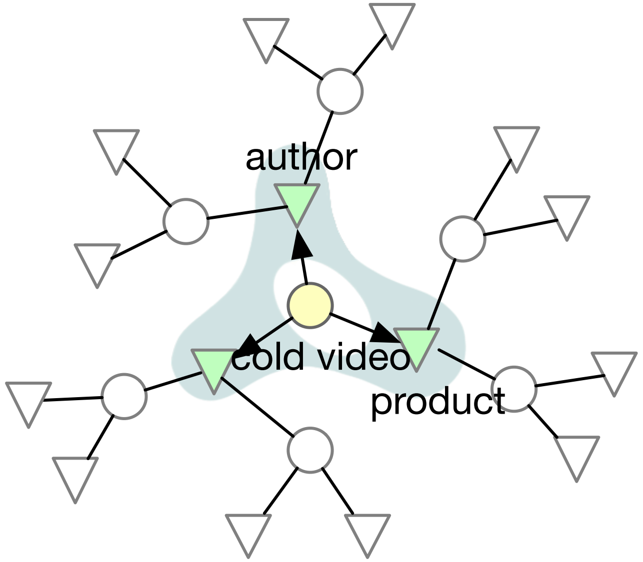


➢ No requirement for user-interaction logs for cold-start video.

➢ 6.82% improvement of click-through-rate (CTR) in Taobao’ s online environment.

Graph Construction: Physical Linkage

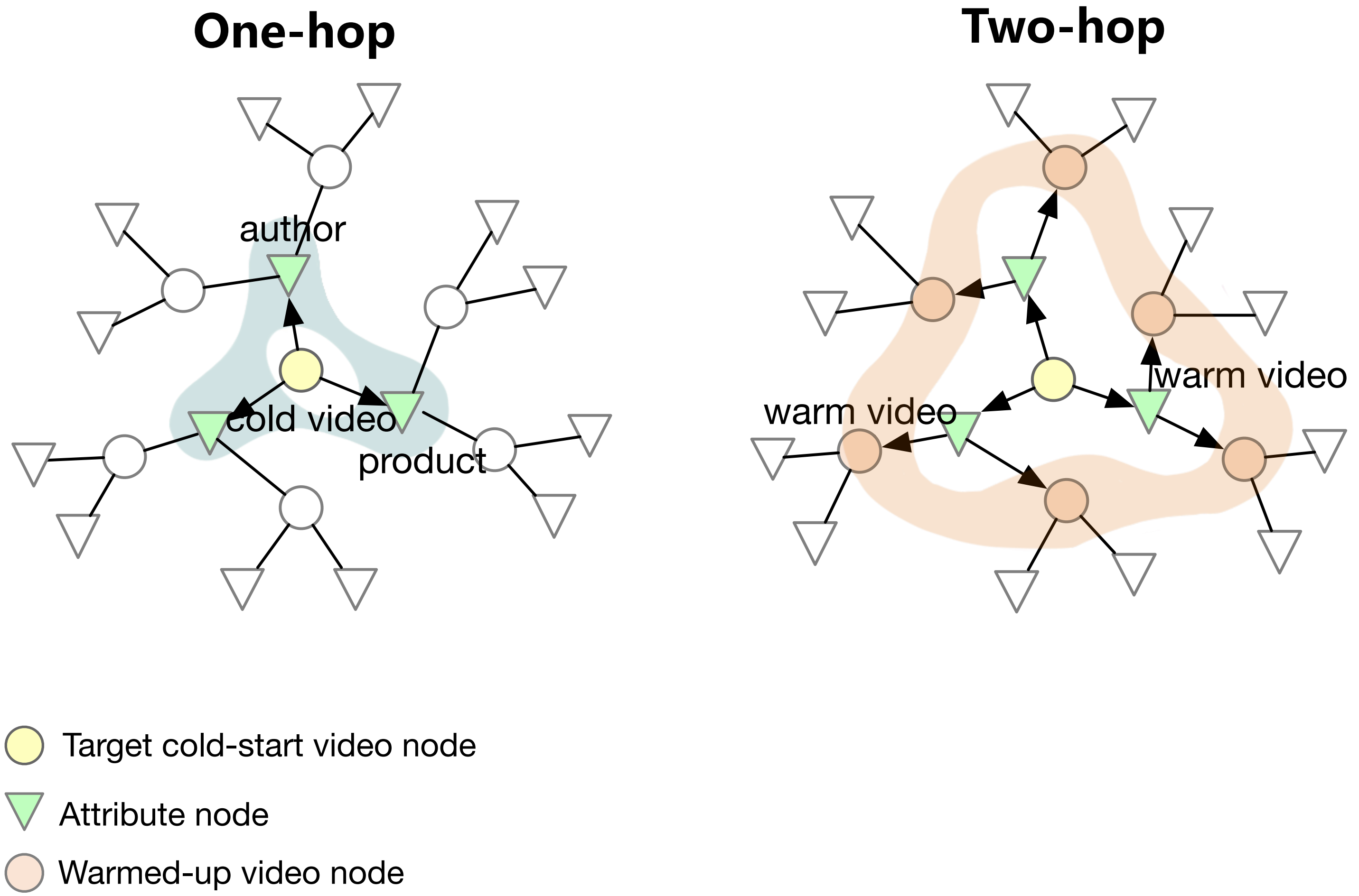
One-hop



Target cold-start video node

Attribute node

Graph Construction: Physical Linkage



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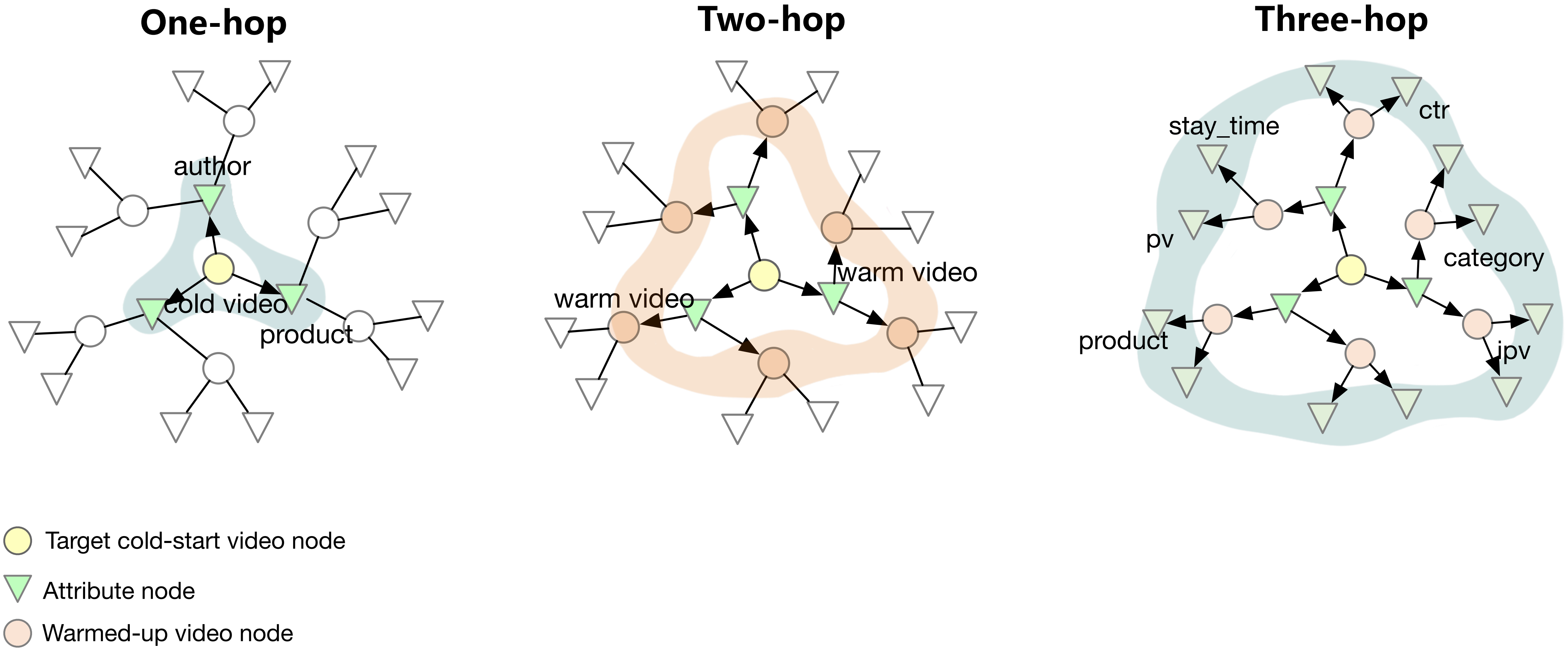

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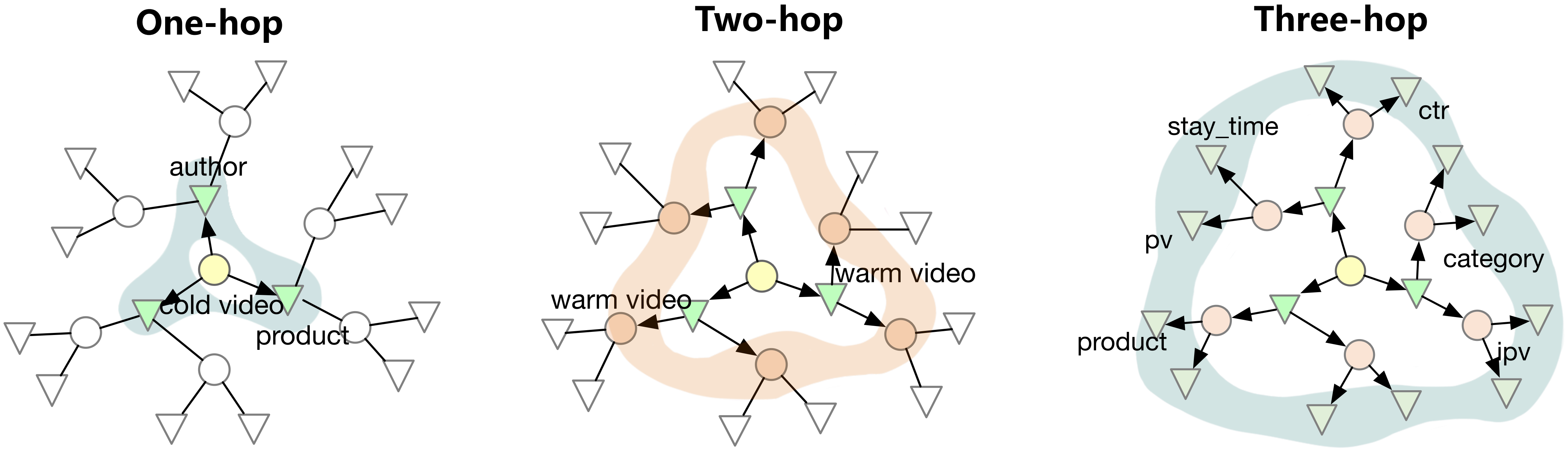


Pros:

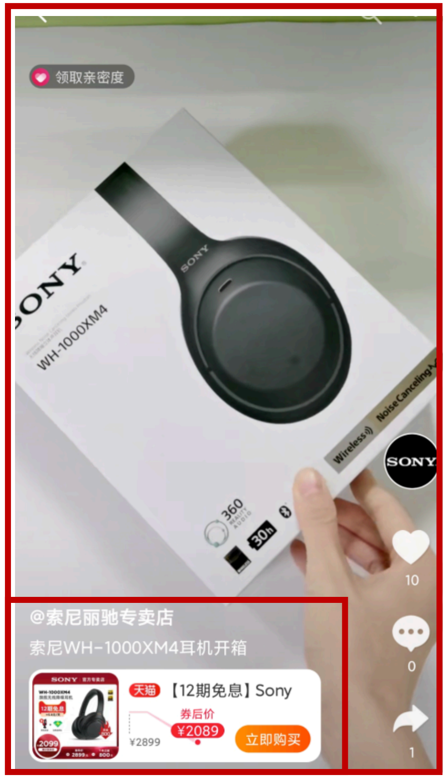
- ➢ Can link 95% cold videos to at least one warm video.
- ➢ Share similar content or style with neighbored videos.

Cons:

- ➢ Cannot assure all cold-videos can link to enough warm videos (>= 5)
- ➢ Cannot guarantee the highest semantic similarity

Graph Construction: Semantic Linkage

Title & Cover image



Tan, Hao, and Mohit Bansal. "Lxmert: Learning cross-modality encoder representations from transformers." arXiv preprint arXiv:1908.07490 (2019).

Graph Construction: Semantic Linkage

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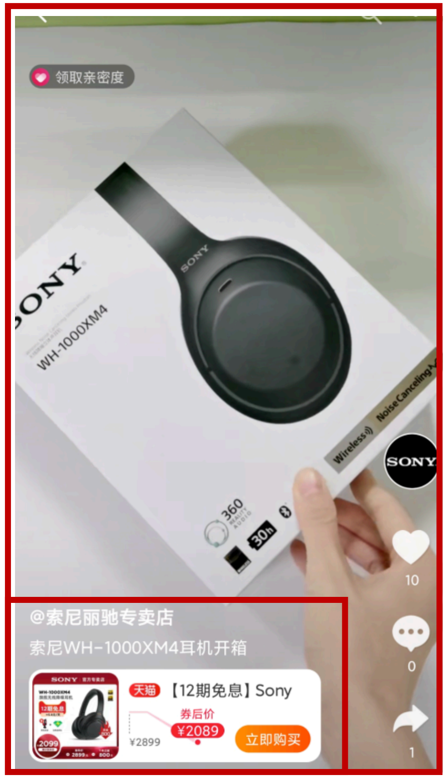
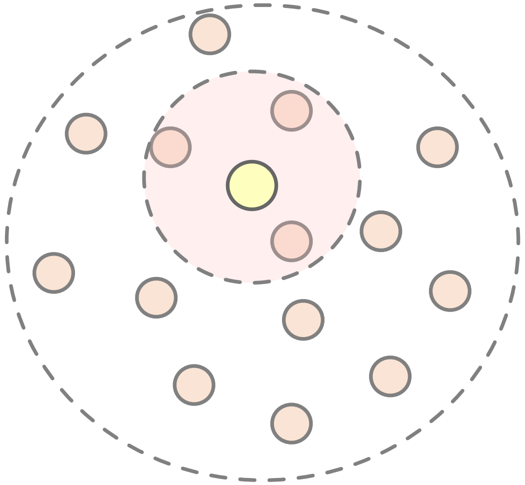


Semantic embedding



Top-k similarity
in semantic space

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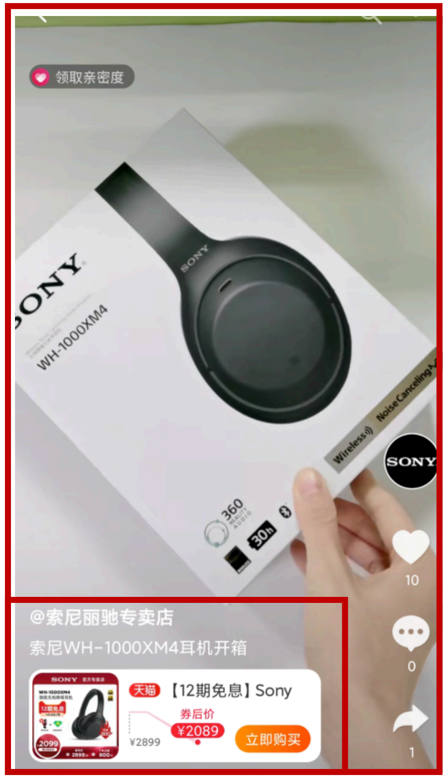

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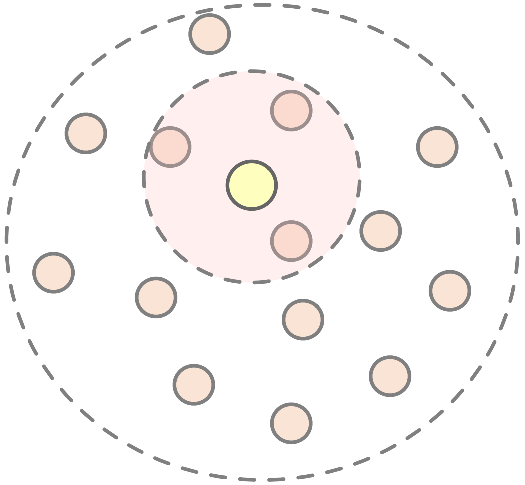

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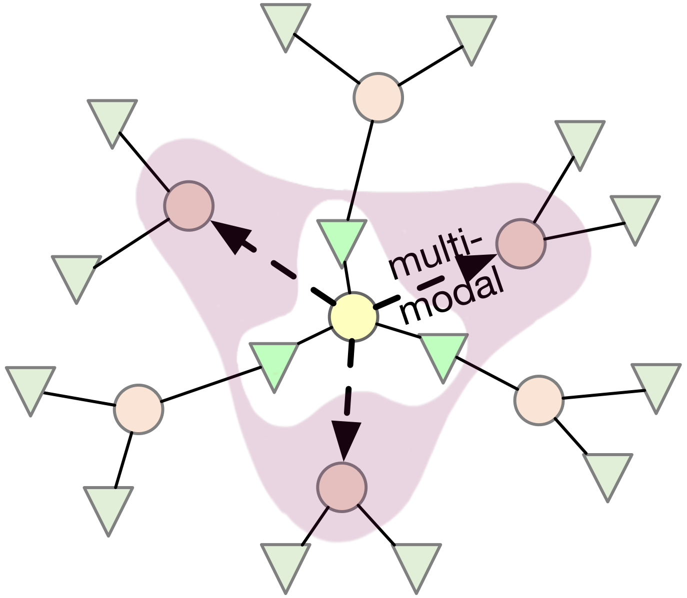


k=20 in our scenario

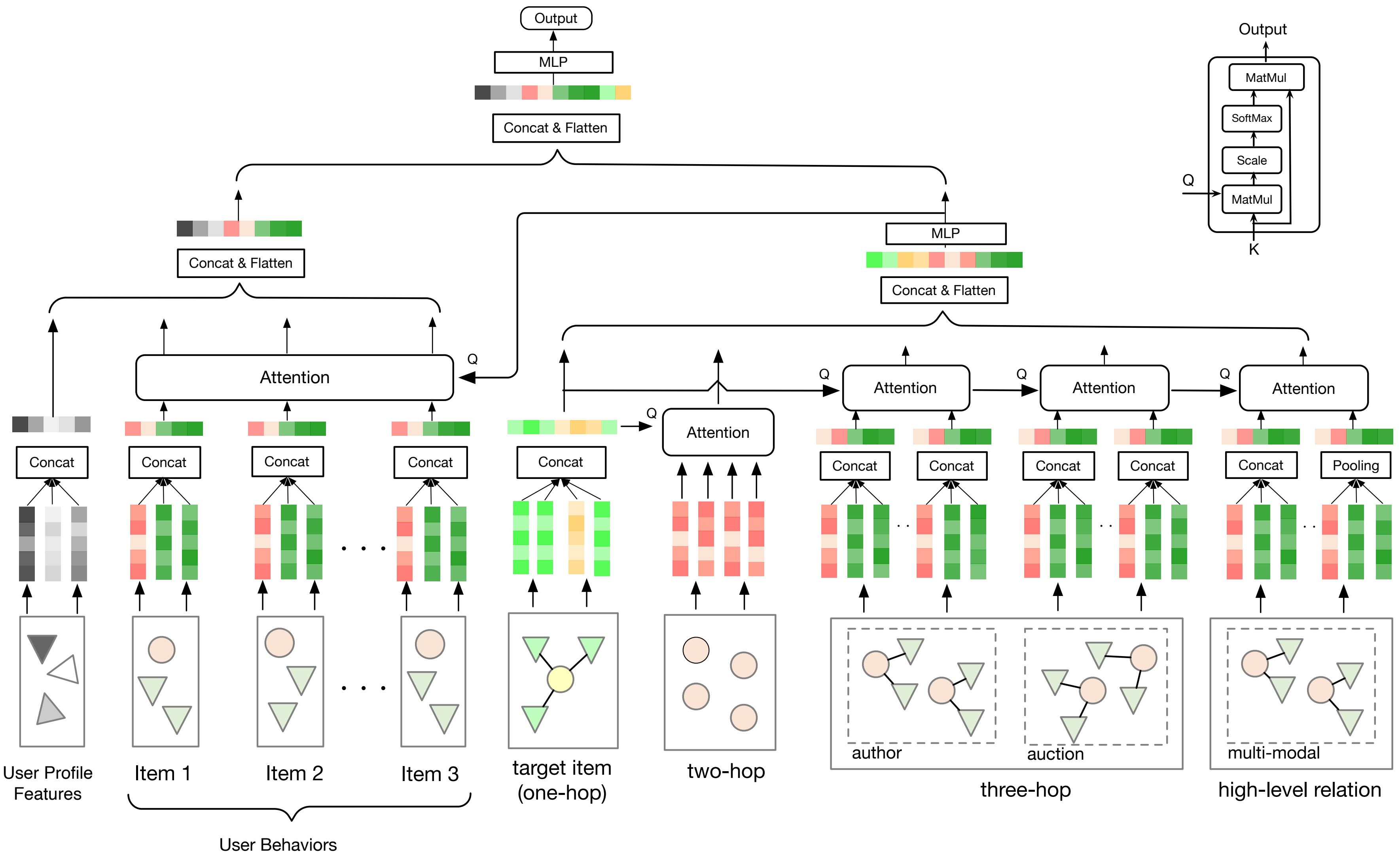
Tan, Hao, and Mohit Bansal. "Lxmert: Learning cross-modality encoder representations from transformers." arXiv preprint arXiv:1908.07490 (2019).

A case study

(a) Target Video (b) Same Item

(c) Same Author (d) Semantic Similar

GIFT: Graph-guIded Feature Transfer Network



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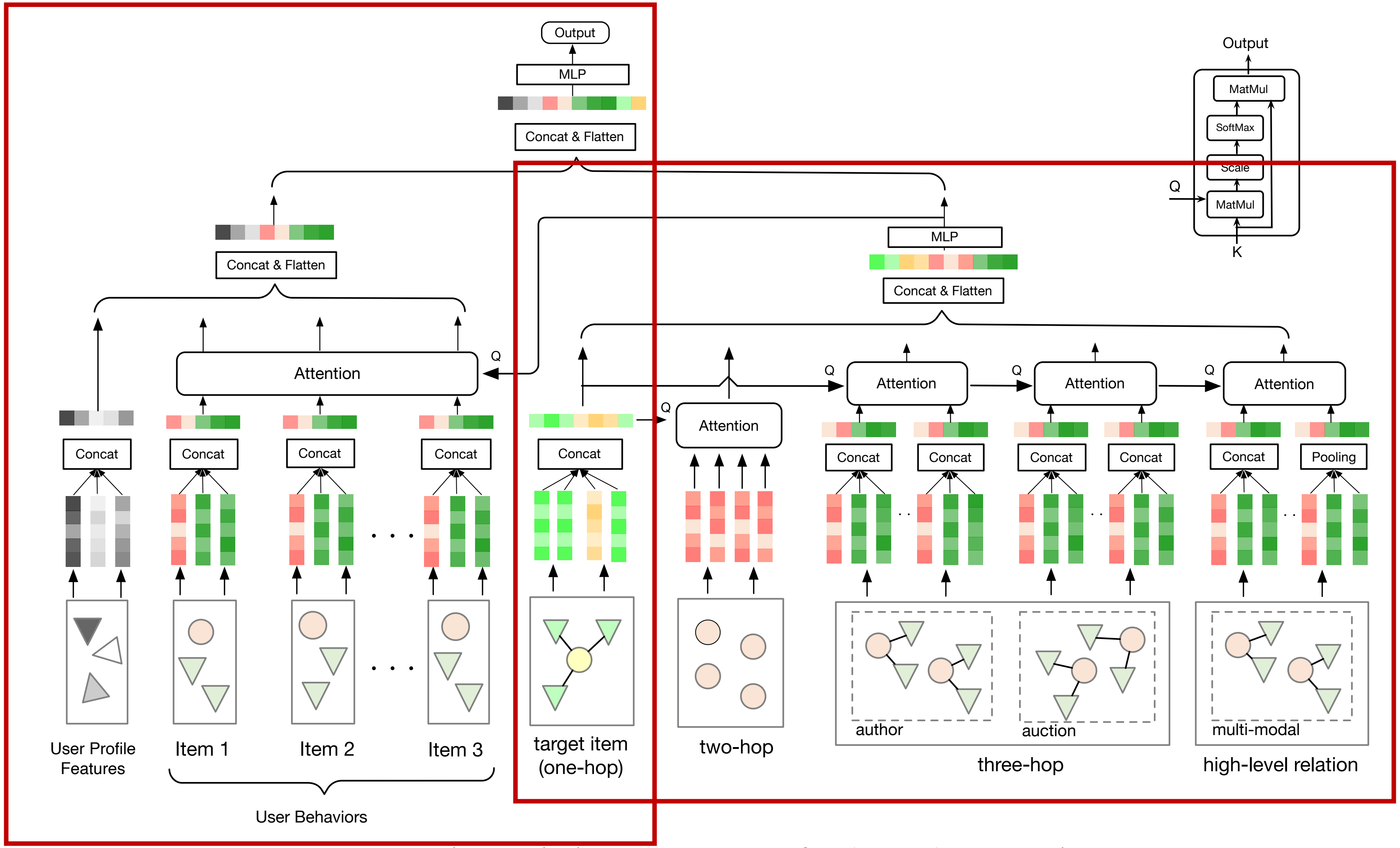

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Zhou, Guorui, et al. "Deep interest network for click-through rate prediction." *Proceedings of the 24th ACM SIGKDD* 2018.

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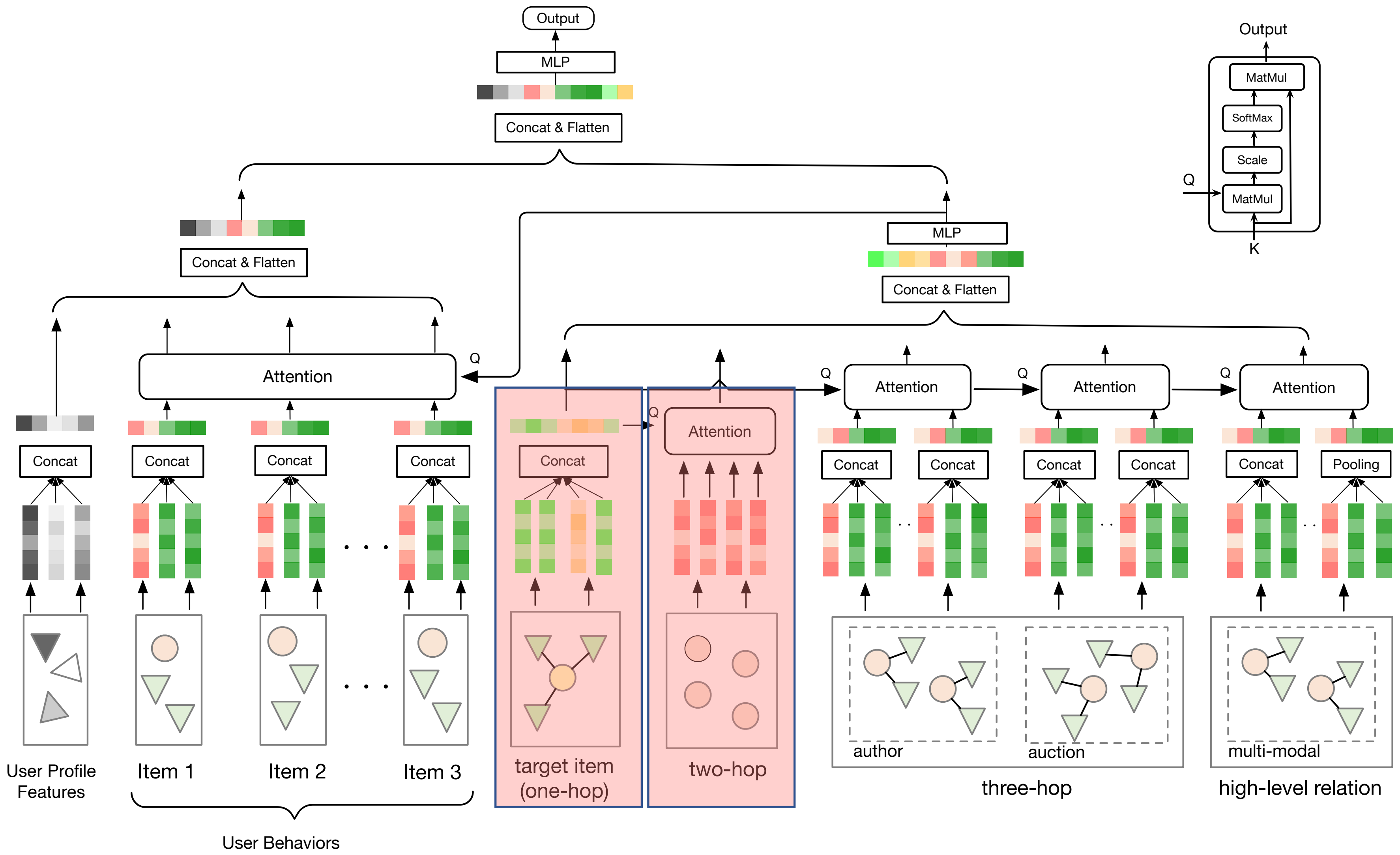

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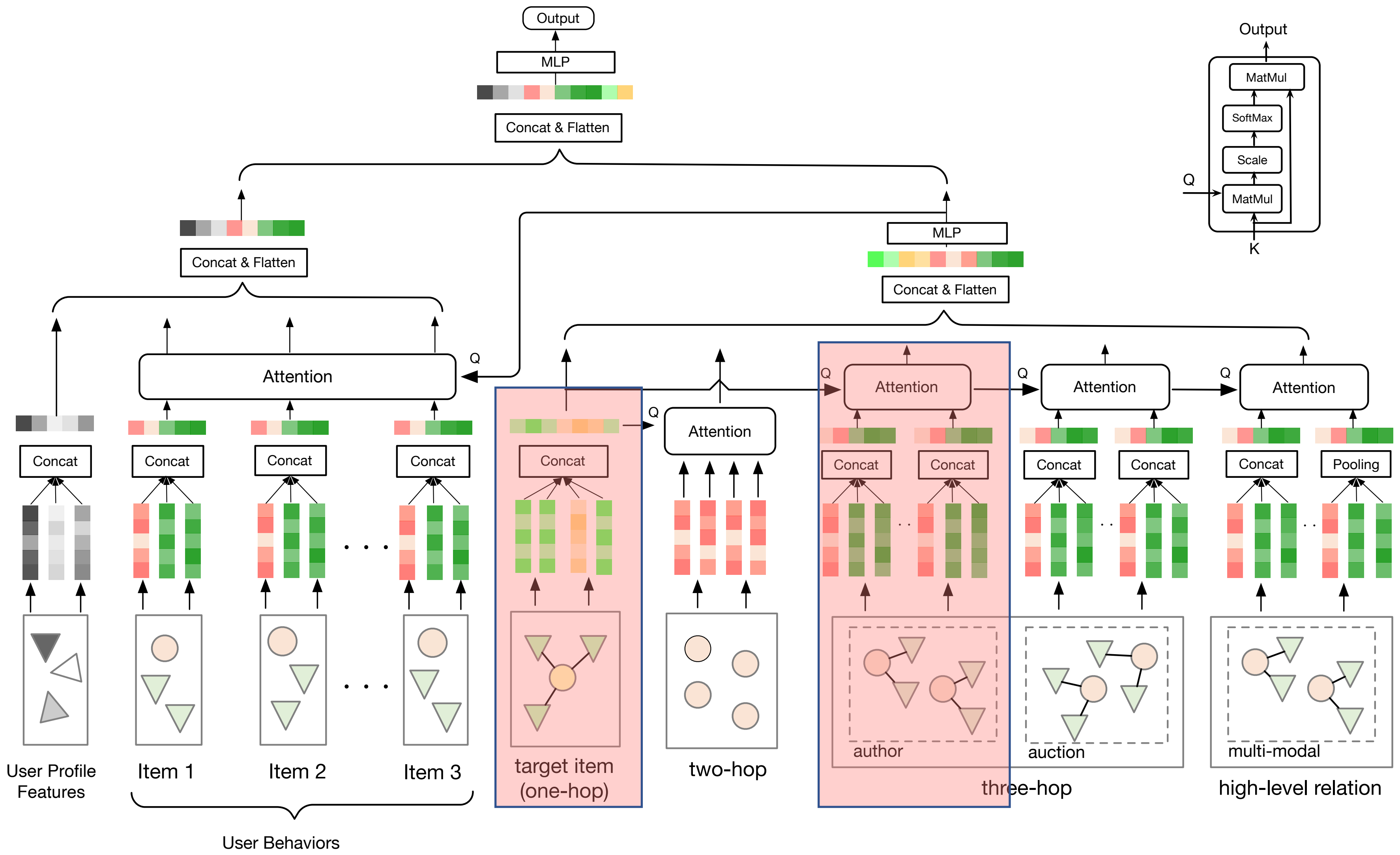

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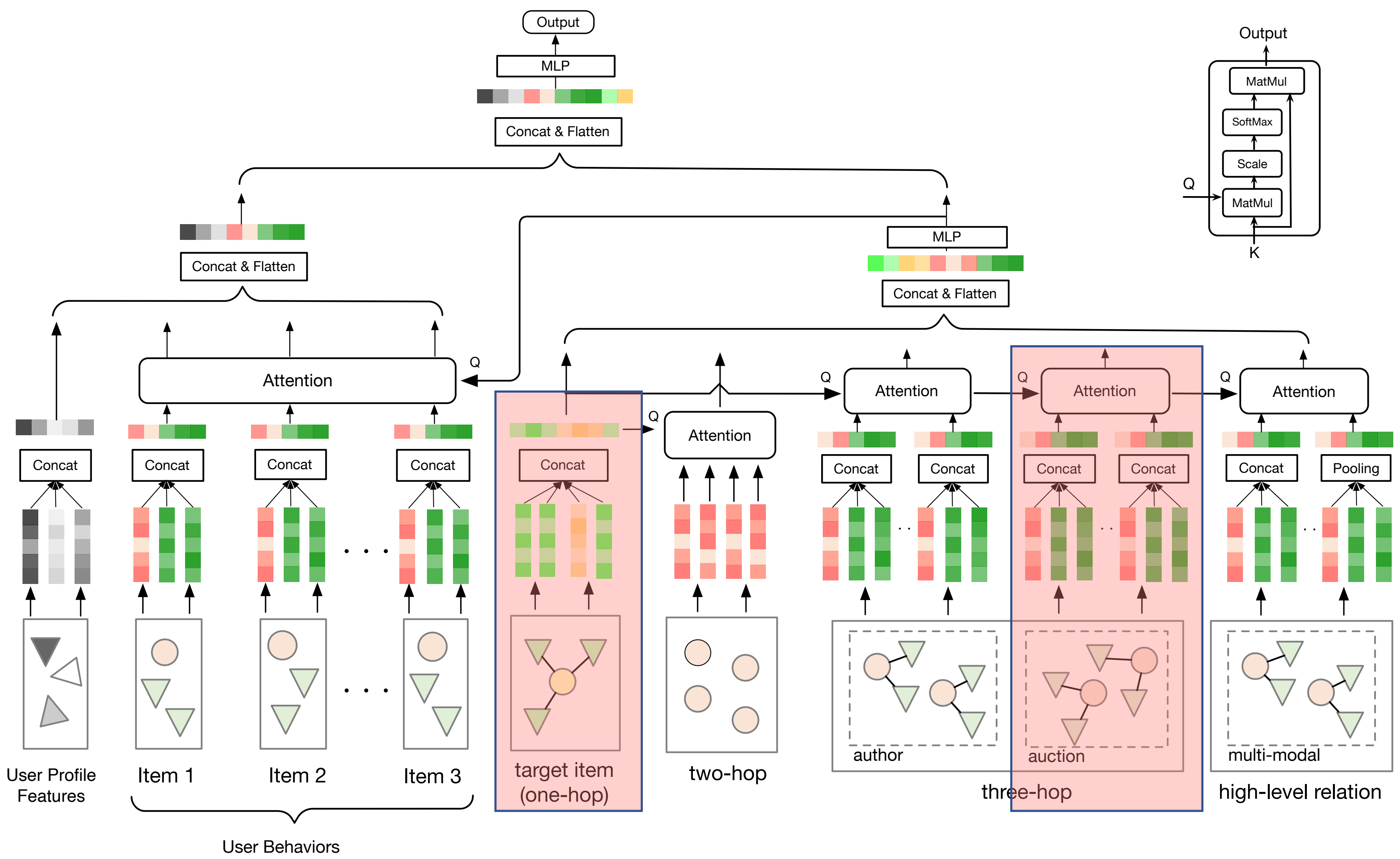

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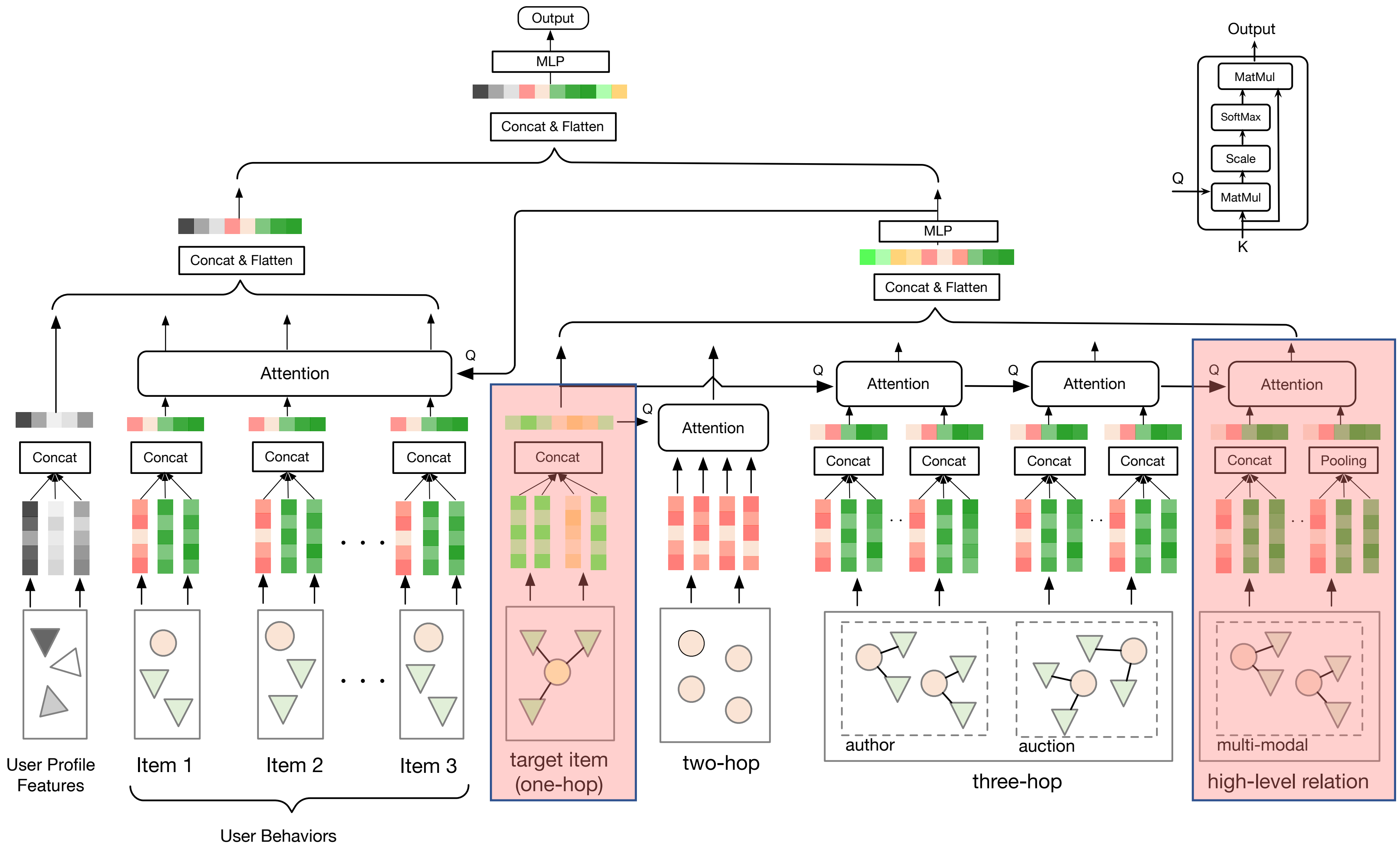

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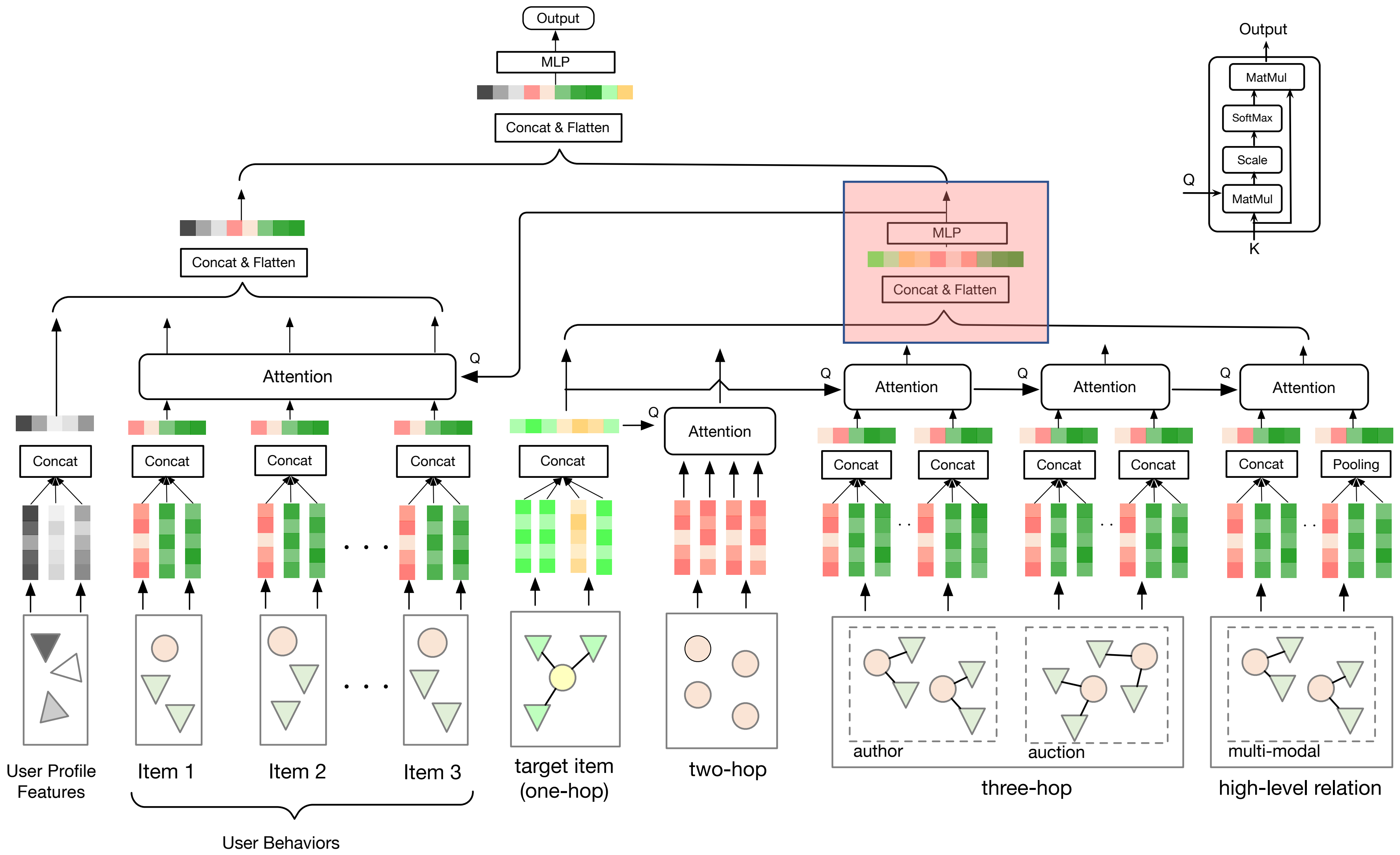

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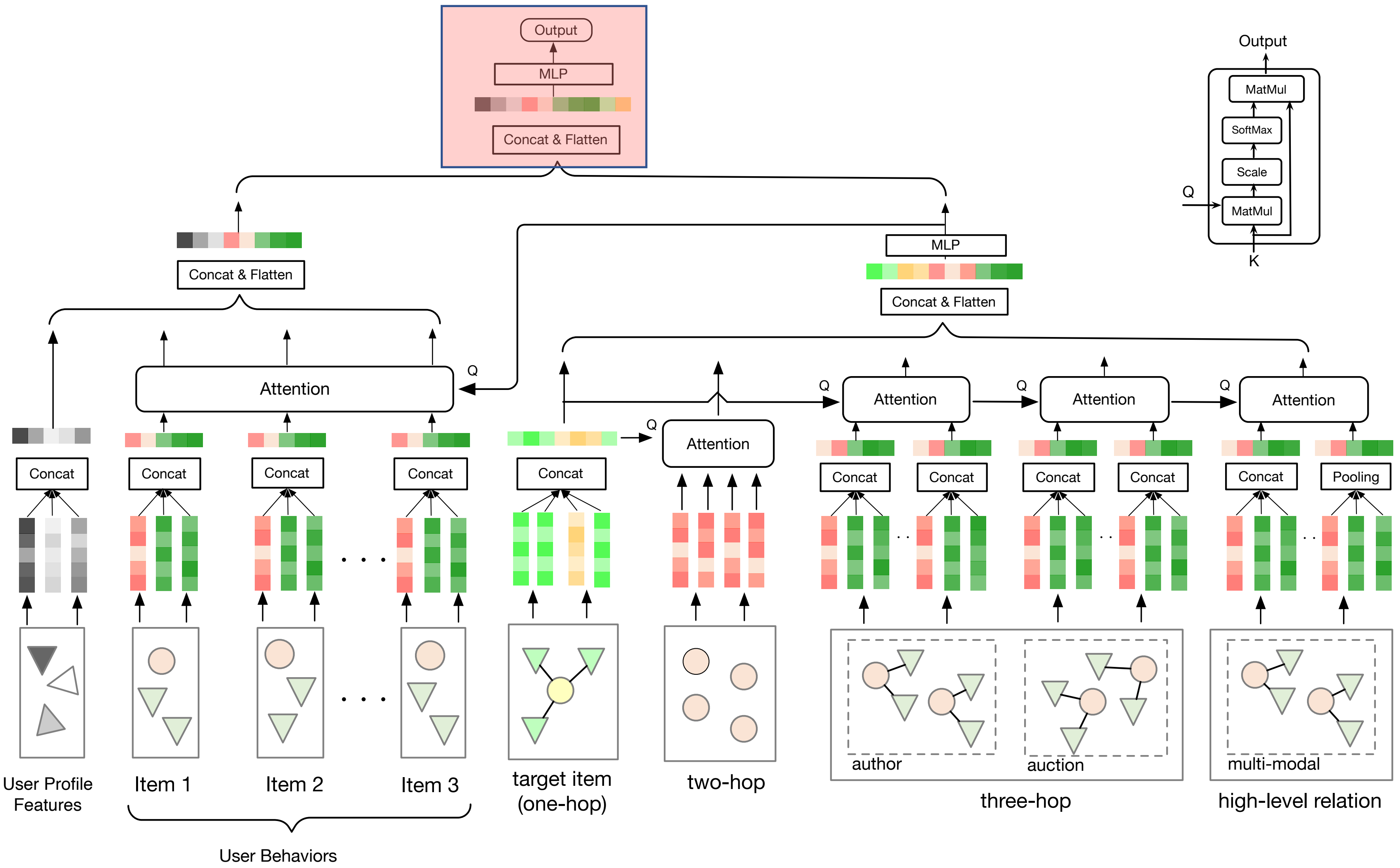

Graph-guIded Feature Transfer (GIFT) network

System Implementation and Deployment

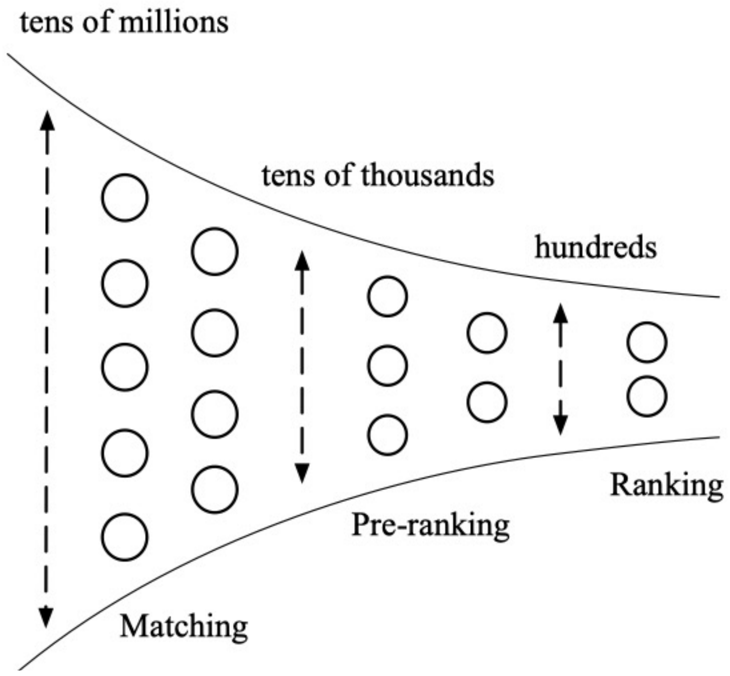

Figure 4: The cascade architecture of industrial recommendation system.

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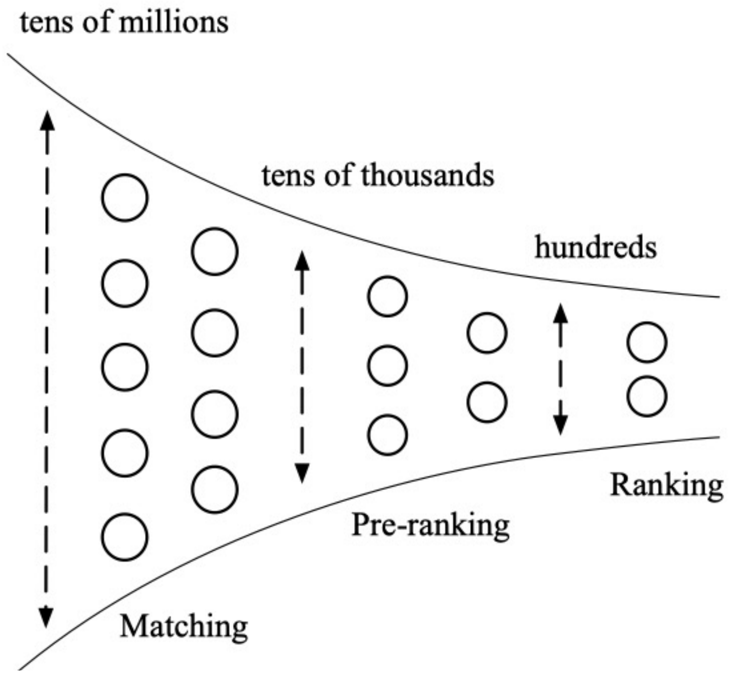

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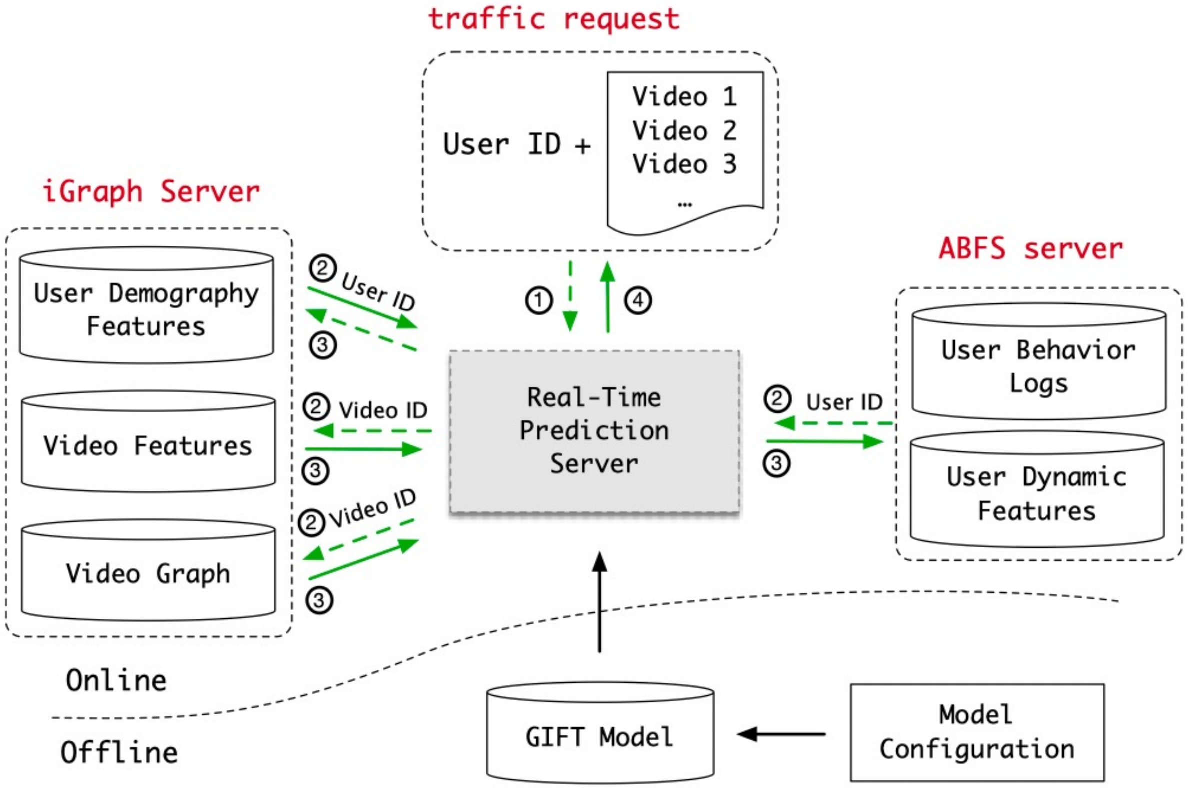

Figure 5: The overall framework of GIFT system deployed in Taobao.

Experiments

Dataset

Table 1: Statistics of Taobao Dataset

Dataset		# Users	# Items	# Samples	Edge Type	# Edges	Path Type	# Paths
Taobao	full	4.98×10^7	2.2×10^7	5.78×10^8	V-A	2.2×10^7	V-A-V	1.9×10^8
	cold	3.0×10^7	4.8×10^5	1.38×10^8	V-P	2.1×10^7	V-P-V	5.7×10^7
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Comparison

Table 2: Performance Comparison

Methods \ Metrics		AUC	RelaImpr
Handcrafted Features	LR	0.7218	-13.63%
	SVM	0.7339	-8.92%
	GBDT	0.7377	-7.44%
DNNs	DNN	0.7423	-5.65%
	Wide&Deep	0.7465	-4.01%
	DeepFM	0.7508	-2.33%
	DIN	<u>0.7568</u>	<u>0.00%</u>
Cold-Start Methods	DropOutNet	0.7573	0.19%
	ACCM	0.7550	-0.70%
Ours	**GIFT**	**0.7670**	**3.97%**
	GIFT[1]	**0.7693**	**4.87%**

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Experiments: extend to other methods

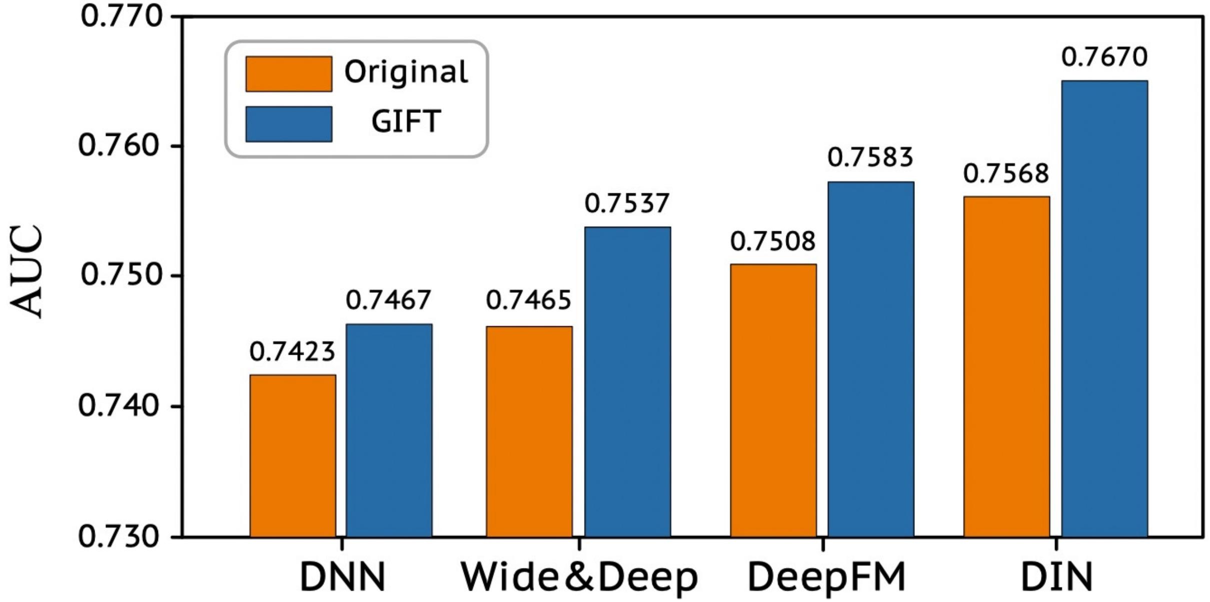

Figure 6: Performance (AUC) comparison of different models enhanced by our GIFT method on Taobao dataset.

Production Environment Experiment

Online A/B Test (Sep. 21, 2020, to Sep. 27, 2020, in the homepage of Taobao App)

Click Through Rate

Baseline	GIFT	Impr.
4.180%	4.465%	**6.82**%

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Response Time

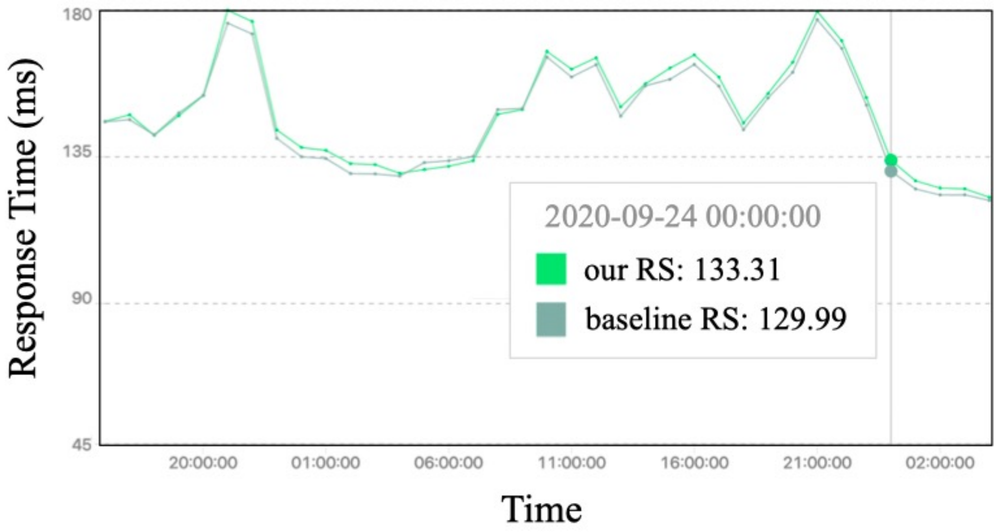

Figure 7: Comparison of Online Response Time

Code

https://github.com/Bayi-Hu/GIFT-Graph-guided-Feature-Transfer-Network

Thanks for listening

Paper

https://arxiv.org/pdf/2202.11525.pdf