

1. [Abstract.](#)
2. [1 Introduction](#)
3. [2 Methodology](#)
 1. [2.1 Problem Formulation](#)
 2. [2.2 Dual-path Interest Modeling](#)
 1. [2.2.1 Intent Localization \(Retroactive Suppression\)](#)
 2. [2.2.2 Personalized Rhythm Retrieval](#)
 3. [2.3 Adaptive Satiation Gating Unit \(ASGU\)](#)
 4. [2.4 Satiation-aware Attention](#)
 5. [2.5 TTNP Auxiliary Task and Training](#)
4. [3 Experiments](#)
 1. [3.1 Experimental Setup](#)
 1. [3.1.1 Datasets](#)
 2. [3.1.2 Evaluation Metrics](#)
 3. [3.1.3 Competitors](#)
 2. [3.2 Experimental Results](#)
 1. [3.2.1 SOTA Comparison](#)
 2. [3.2.2 Ablation Study](#)
5. [4 Conclusion](#)
6. [5 Acknowledgments](#)
7. [References](#)

[License: arXiv.org perpetual non-exclusive license](#)

arXiv:2607.12714v1 [cs.IR] 14 Jul 2026

\setccotype

by

Learning to Forget: Satiation-Aware Long-Sequence Transducers for Mitigating Post-Purchase Redundancy

Yipin Dai Alibaba GroupHangzhouChina 220245072@seu.edu.cn , Rucong Tang Alibaba GroupHangzhouChina tangrucong.trc@taobao.com , Xing Fang Alibaba GroupHangzhouChina fangxing.fx@taobao.com , Yang Huang Alibaba GroupHangzhouChina hy234680@taobao.com , Jing Wang Alibaba GroupHangzhouChina jing.wangj1@taobao.com , Zhentao Song Alibaba

Abstract.

Sequential recommendation models predominantly interpret user interactions as positive signals for preference accumulation. However, in e-commerce scenarios, a purchase action often signifies the termination of a specific intent ("Interest Exit") rather than its continuation. Existing models overlook this distinction, suffering from Action-Intent Asymmetry, which leads to severe post-purchase redundancy. In this paper, we propose the Satiation-Aware Mechanism (SAM), an end-to-end framework designed to explicitly model the lifecycle of user interests. SAM incorporates three key components: (1) A Dual-path Cross-Attention architecture that retroactively suppresses historical clicks associated with a fulfilled intent while simultaneously retrieving personalized replenishment rhythms from long-term purchase history; (2) An Adaptive Satiation Gating Unit (ASGU) that generates a time-sensitive soft mask to inhibit satisfied interests immediately after purchase and gradually "re-awaken" them as the predicted repurchase cycle approaches; and (3) A self-supervised Time-to-Next-Purchase (TTNP) auxiliary task to learn latent product lifecycles without manual annotation. Extensive offline experiments on industrial datasets and online A/B testing demonstrate that SAM significantly reduces the Post-Purchase Repeat Rate (PPRR) by over 60%.

Recommender Systems, User Behavior Modeling

^{††}journalyear: 2026^{††}copyright: cc^{††}conference: Proceedings of the 49th International ACM SIGIR Conference on Research and Development in Information Retrieval; July 20–24, 2026; Melbourne, VIC, Australia^{††}booktitle: Proceedings of the 49th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '26), July 20–24, 2026, Melbourne, VIC, Australia^{††}isbn: 979–8–4007–2599–9/2026/07^{††}doi: 10.1145/3805712.3808427^{††}ccs: Information systems Recommender systems

1. Introduction

Modern recommender systems and advertising platforms increasingly rely on long behavioral sequences to infer users' evolving intent. Transformer-style self-attention has become the dominant paradigm due to its capability to capture long-range dependencies and perform efficient parallel computation (Vaswani et al., 2017). In sequential recommendation, models such as SASRec and BERT4Rec represent the state-of-the-art for next-item prediction (Kang and McAuley, 2018; Sun et al., 2019). Similarly, in industrial CTR/ranking scenarios, architectures like DIN and DIEN model candidate-aware activation and interest evolution over rich behavior histories, demonstrating production viability at scale (Zhou et al., 2018, 2019).

However, in e-commerce scenarios where purchase events are semantically critical, current systems overlook a fundamental phase in the user interest lifecycle: Interest Exit. While standard attentive models excel at capturing interest evolution and accumulation, they fail to model the

termination of an intent. This deficiency leads to what we term Action–Intent Asymmetry: a single purchase action often signifies the satisfaction and consequent closure of a broader underlying intent (manifested as a cluster of preceding clicks). Yet, standard self–attention mechanisms treat the purchase merely as another positive signal to be aggregated for future reinforcement (*Li et al.*, [2020](#)). This inability to recognize ”Interest Exit” results in a persistent challenge known as post–purchase redundancy, where fulfilled intents linger in the user representation, causing the system to recommend identical items immediately after conversion, thereby wasting premium recommendation slots and degrading user trust.

The difficulty in modeling Interest Exit lies in the inherent complexity of Satiation Dynamics. The ”exit” is rarely a binary event but a continuous process governed by product–specific lifecycles and user habits. First, the duration of satiation varies significantly: the purchase of a durable good (e.g., a refrigerator) typically signals a permanent or long–term exit of that intent, whereas a consumable (e.g., paper towels) implies a temporary exit with a latent, periodic resurrection need. Second, user consumption styles are diverse, ranging from ”serial buying” to single–transaction satisfaction. Existing solutions often rely on post–hoc reranking rules (e.g., MMR (*Carbonell and Goldstein*, [1998](#)), DPP (*Kulesza and Taskar*, [2012](#))) or heuristic probabilities between repeat and explore modes (*Ren et al.*, [2019](#)). While effective to some extent, these approaches operate outside the representation learning process and lack the granularity to model item–level satiation decay and the ”lead–in” effects required for accurately predicting the re–emergence of an interest.

To tackle this issue, we propose the Satiation–Aware Mechanism (SAM), an end–to–end framework designed to explicitly model the lifecycle of user interests. Unlike previous methods that treat interactions uniformly, SAM introduces a Dual–path Cross–Attention architecture to decouple intent localization from rhythm estimation. First, to address Action–Intent Asymmetry, we design a retroactive suppression mechanism that uses the purchased item as a probe to identify and suppress not only the purchase event itself but also the relevant pre–purchase browsing history. Second, to capture personalized product lifecycles, we retrieve replenishment rhythms from a separate long–term purchase sequence (S_{buy}). These signals are fused into our proposed Adaptive Satiation Gating Unit (ASGU). ASGU functions as a soft, time–sensitive mask within the attention layer: it suppresses attention to satisfied interests immediately after purchase and gradually ”re–awakens” them as the elapsed time approaches the predicted cycle, controlled by a learnable lead–in offset.

A central challenge in SAM is learning accurate cycle embeddings without explicit manual labels (e.g., labeling items as ”durable” or ”consumable”). Drawing inspiration from continuous–time event modeling (*Du et al.*, [2016](#); *Mei and Eisner*, [2017](#)), we introduce a self–supervised auxiliary task: Time–to–Next–Purchase (TTNP). By mining repurchase segments from raw logs and predicting the time gap to the next equivalent action, TTNP aligns the latent cycle embeddings with real–world repurchase rhythms, enabling ASGU to learn personalized ”exit strength” across different users and categories.

In summary, our main contributions are:

•

Satiation-Aware Paradigm: We identify the Action-Intent Asymmetry problem and propose an end-to-end representation learning framework that treats purchase as a signal for intent termination rather than just accumulation.

•

Dual-path SAM Architecture: We propose the Satiation-Aware Mechanism featuring a Dual-path structure. It combines retroactive suppression (to locate past exploratory clicks) with retrieval-based rhythm estimation (to model long-term habits).

•

Adaptive Gating & TTNP Supervision: We design the ASGU with a "lead-in" mechanism to balance redundancy suppression and repurchase recall, supervised by a Time-to-Next-Purchase auxiliary task that learns latent product lifecycles without manual annotation.

Empirically, SAM effectively mitigates post-purchase redundancy while improving long-term accuracy metrics on industrial-scale datasets, demonstrating that "knowing when to forget" is as crucial as "knowing what to remember." By implementing our framework, we enable models to autonomously determine when an interest thread should exit the active representation, effectively mitigating to the post-purchase redundancy problem.

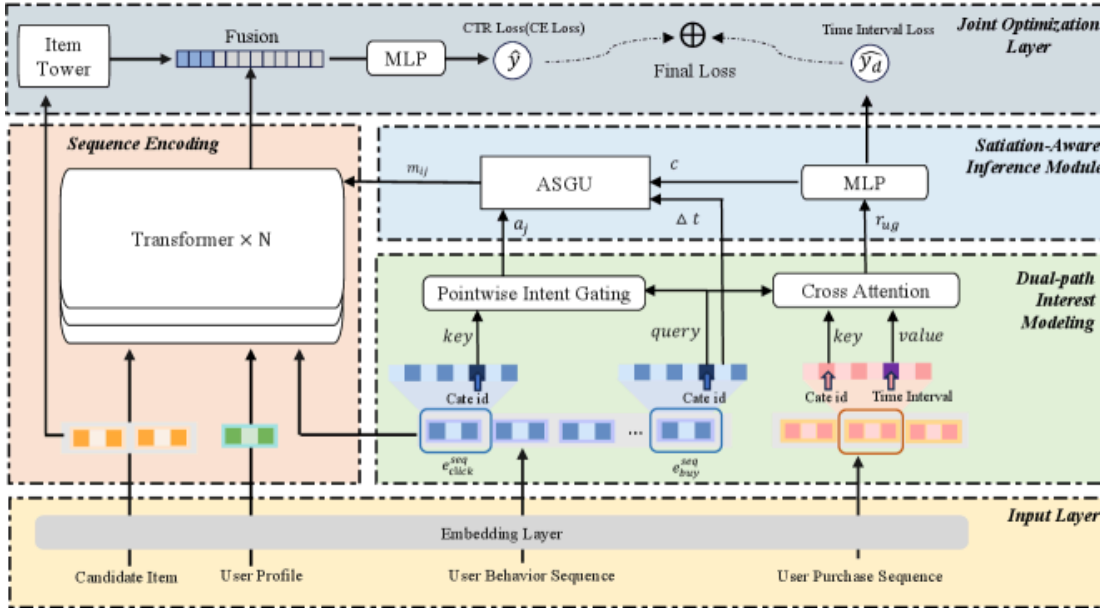


Figure 1. The overall architecture of the Satiation-Aware Mechanism (SAM).

2. Methodology

We propose the Satiation-Aware Mechanism (SAM) to explicitly model the Interest Exit phenomenon in sequential recommendation. Unlike heuristic rule-based filtering, SAM learns personalized satiation cycles and retroactively suppresses historical intents in an end-to-end manner. The architecture consists of three core components: (1) a Dual-path Cross-Attention

module for intent localization and rhythm retrieval, (2) an Adaptive Satiation Gating Unit (ASGU) for dynamic mask generation, and (3) a Satiation-aware Attention layer for logit-level intervention. As illustrated in Figure 1, the SAM framework follows a multi-tower fusion architecture.

2.1. Problem Formulation

In the ranking stage of an industrial recommendation system, the objective is to estimate the Click-Through Rate (CTR) for a specific candidate item. Formally, given a user u , we define the inputs as follows: 1) User Profile P_u , which includes static features such as demographics and long-term preferences; 2) User Behavior Sequence $S = \{x_1, \dots, x_L\}$, a chronological sequence of clicks and purchases where each interaction x_j contains item features and the category g_j ; 3) User Purchase Sequence $S_{\text{buy}} = \{x_1^{(p)}, \dots, x_H^{(p)}\}$, a long-term history filtering only purchase events to capture consumption rhythms; and 4) Candidate Item i , the target item to be scored with category g_i .

The goal is to learn a scoring function $f(P_u, S, S_{\text{buy}}, i) \rightarrow \hat{y}$, where $\hat{y} \in [0, 1]$ represents the probability of interaction. Our specific focus is to correctly identify “Interest Exit” events within S to suppress the score $\hat{y}$ when candidate i belongs to a category the user has recently satisfied.

2.2. Dual-path Interest Modeling

To address the Action-Intent Asymmetry, we employ a dual-path cross-attention mechanism that simultaneously identifies “what to suppress” and “how long to suppress.” To ensure semantic consistency and parameter efficiency, both paths share the same projection matrices (W_Q, W_K).

2.2.1. Intent Localization (Retroactive Suppression)

A purchase signals the fulfillment of an entire intent cluster. To avoid the weight dilution inherent in Softmax for long sequences (e.g., $L = 500$), we define the intent attribution weight a_j as a pointwise similarity gate. We use the category embedding $\mathbf{e}_{g_{\text{buy}}}$ of the purchase as a probe query against the category embeddings $\mathbf{e}_{g_j}$ of historical nodes:

$$(1) \quad a_j = \sigma \left(\frac{(W_Q \mathbf{e}_{g_{\text{buy}}})^\top (W_K \mathbf{e}_{g_j})}{\sqrt{d}} \right)$$

where σ is the Sigmoid function. Unlike Softmax, this pointwise formulation allows a_j to maintain a high suppression strength (near 1.0) for all nodes within the same intent cluster, regardless of sequence length.

2.2.2. Personalized Rhythm Retrieval

Simultaneously, we retrieve the user’s consumption rhythm from the long-term purchase history $S_{\text{buy}} = \{(\mathbf{e}_{g_k}, \mathbf{e}_{\Delta T_k})\}_{k=1}^H$. We employ target-aware cross-attention to compute a rhythm representation $\mathbf{r}_{u,g}$:

$$(2) \mathbf{r}_{u,g} = \sum_{k=1}^H \beta_k \cdot (W_V \mathbf{e}_{\Delta T_k}), \quad \beta_k = \text{Softmax}_k \left(\frac{(W_Q \mathbf{e}_{g_{\text{buy}}})^\top (W_K \mathbf{e}_{g_k})}{\sqrt{d}} \right)$$

where $\mathbf{e}_{\Delta T_k}$ is the embedding of historical time intervals. The resulting $\mathbf{r}_{u,g}$ is a weighted sum of historical paces, which is then decoded by an MLP into a positive scalar $c = \text{Softplus}(\text{MLP}(\mathbf{r}_{u,g}))$, representing the predicted replenishment cycle in days. This cycle c is explicitly supervised by the TTNP auxiliary task (detailed in Section 2.5). The shared W_Q, W_K ensure that the rhythm retrieval and intent localization paths operate within a unified semantic space.

Table 1. Offline and Online comparison results. (Mean $\pm$ Std.) * indicates $p < 0.05$. In the Online A/B section, all metrics are reported as relative percentage improvements/reductions over the deployed baseline (DIN).

Model	Offline Metrics			Online A/B Testing		
	AUC ($\uparrow$)	GAUC ($\uparrow$)	PPRR ($\downarrow$)	Δ CTR ($\uparrow$)	Δ GMV ($\uparrow$)	Δ Bad-Case ($\downarrow$)
Classic Models						
DNN	0.741 $\pm$ 0.001	0.665 $\pm$ 0.002	10.5%	–	–	–
DCN-v2 (<i>Wang et al., 2021</i>)	0.745 $\pm$ 0.001	0.669 $\pm$ 0.001	11.2%	–	–	–
DIN (<i>Zhou et al., 2018</i>) (Baseline)	0.749 $\pm$ 0.001	0.674 $\pm$ 0.001	15.5%	0.00%	0.00%	0.00%
DIN + Fixed-Window Filter	0.745 $\pm$ 0.001	0.670 $\pm$ 0.002	7.7%	–0.2%	–0.3%	–31.9%
Recent SOTA						
HiFormer (<i>Gui et al., 2023</i>)	0.753 $\pm$ 0.002	0.679 $\pm$ 0.002	14.5%	–	–	–
RankMixer (<i>Zhu et al., 2025</i>)	0.754 $\pm$ 0.001	0.680 $\pm$ 0.001	13.8%	–	–	–
HSTU (<i>Zhai et al., 2024</i>)	0.758 $\pm$ 0.001	0.684 $\pm$ 0.001	15.2%	+0.8%	+0.4%	+11.0%
HHFT (<i>Yu et al., 2025</i>)	0.759 $\pm$ 0.002	0.685 $\pm$ 0.002	14.9%	–	–	–
MTGR (<i>Han et al., 2025</i>)	0.761 $\pm$ 0.001	0.687 $\pm$ 0.001	16.1%	–	–	–
OneTrans (<i>Zhang et al., 2025</i>)	0.762 $\pm$ 0.001	0.689 $\pm$ 0.001	15.8%	+1.1%	+0.6%	+10.2%

SAM (Ours)	0.763* $\pm$ 0.001	0.691* $\pm$ 0.001	4.1%	+1.1%	+0.9%	−74.5%
------------	--------------------	--------------------	------	-------	-------	--------

2.3. Adaptive Satiation Gating Unit (ASGU)

The ASGU generates a satiation mask m_{ij} to modulate historical nodes. To balance immediate redundancy suppression with future demand forecasting, we design the mask to be deepest right after purchase and gradually release as it approaches the predicted cycle c :

$$(3) \quad m_{ij} = 1 - a_j \cdot \underbrace{\sigma\left(k \cdot \left(\alpha - \frac{\Delta t_{ij}}{c}\right)\right)}_{\text{Satiety Function } \phi}$$

where Δt_{ij} is the elapsed time since purchase and k is a learnable steepness factor.

Specifically, in the Satiety Phase, when $\Delta t_{ij} \rightarrow 0$, the term $(\alpha - \frac{\Delta t}{c}) \approx \alpha$. Given $\alpha \in (0, 1]$ is a Lead-in Offset (e.g., 0.8), ϕ remains high, leading to $m_{ij} \approx 1 - a_j$. For identical categories ($a_j \approx 1$), the node is effectively masked ($m_{ij} \rightarrow 0$). During the Recovery Phase, as Δt_{ij} approaches the threshold αc , the term inside σ nears 0, causing $\phi \rightarrow 0.5$ and the mask to fade. Finally, for Pre-purchase Recall, once $\Delta t_{ij} > \alpha c$, ϕ drops towards 0, and $m_{ij} \rightarrow 1$. This “lead-in” mechanism ensures that the model can re-activate historical interests slightly before the predicted cycle c ends to capture early browsing for replenishment.

2.4. Satiation-aware Attention

To maintain numerical stability, we inject the gating signal as a Logit-bias Mask. For any query i and key j , the modified attention logit ℓ_{ij} is formulated as:

$$(4) \quad \ell_{ij} = \frac{\mathbf{q}_i^\top \mathbf{k}_j}{\sqrt{d}} + \log(\text{clip}(m_{ij}, \epsilon, 1))$$

This ensure that when $m_{ij} \rightarrow 0$, the corresponding attention weight $\alpha_{ij} \rightarrow 0$.

2.5. TTNP Auxiliary Task and Training

To ground the latent cycle c in physical time, we introduce the Time-to-Next-Purchase (TTNP) auxiliary task. For a sequence of purchases of the same category g at times t_k and t_{k+1} , the model minimizes a censored regression loss:

$$(5) \quad \mathcal{L}_{\text{aux}} = \sum |\log(c + 1) - \log(\Delta t + 1)|^2$$

where $\Delta t = t_{k+1} - t_k$ is the target interval to the next purchase. Crucially, to handle right-censored cases where a user only has a single purchase of category g without a subsequent purchase in our observation window, we impute the missing Δt using the platform’s global average repurchase cycle $\bar{c}_g$ for that category. Specifically, we set $\Delta t = \max(T_{\text{end}} - t_k, \bar{c}_g)$, where

T_{end} is the end of the data window. This ensures the model learns a robust lower bound even for sparse, long-cycle durables.

The total loss is a joint optimization: $\mathcal{L} = \mathcal{L}_{\text{CTR}} + \lambda \mathcal{L}_{\text{aux}}$.

3. Experiments

3.1. Experimental Setup

3.1.1. Datasets

We collected and sampled the online service logs from the online Tmall e-commerce platform between 2025/06/07 to 2025/11/07 to construct the experimental dataset $\mathcal{D}$. As shown in Table 2, the entire dataset is split chronologically into a training set $\mathcal{D}_{\text{train}}$ (first 5 months) and a testing set $\mathcal{D}_{\text{test}}$ (last 1 month) to prevent data leakage. We filter for active users with at least 20 interactions and truncate sequences to length $L = 500$.

Table 2. Statistics of the established Industrial Logs.

Dataset #Users #Items #Actions #Purchases

$\mathcal{D}_{\text{train}}$ 11.52M 7.82M 190.33M 9.06M

$\mathcal{D}_{\text{test}}$ 6.13M 4.65M 52.74M 3.22M

3.1.2. Evaluation Metrics

Since we focus on the fine-ranking stage (CTR prediction), we adopt a comprehensive set of metrics to evaluate both accuracy and diversity. For Ranking Accuracy, we utilize AUC (Area Under ROC Curve) to measure global ranking capability and GAUC (Group AUC) to assess quality within each user’s personalized list, the latter being more indicative of online performance in industrial systems (Zhou et al., 2018). Beyond accuracy, we introduce Redundancy Control metrics to quantify the “Interest Exit” capability: PPRR (Post-Purchase Repeat Rate) tracks the global percentage of impressions where the recommended item shares the exact same leaf-category as the user’s most recent purchase, computed within a category-specific time window drawn from a pre-existing repurchase cycle lookup table (Carbonell and Goldstein, 1998; Kulesza and Taskar, 2012). Meanwhile, the Bad-Case Ratio is a direct online business metric: it measures the proportion of “already purchased” reasons among all explicit negative feedback events (e.g., clicking “dislike”) submitted by users. For online A/B testing, we monitor CTR and GMV on complementary items to ensure balanced business growth.

3.1.3. Competitors

We compare SAM against a comprehensive set of baselines categorized into three groups. The first group consists of Classic & Interaction Models, including standard DNN (Cheng et al., 2016; Covington et al., 2016), DCN-v2 (Wang et al., 2021), and DIN (Zhou et al., 2018), which focus on feature interactions and candidate-relevant user interests. The second group covers Efficient

Sequence Models such as HiFormer (Gui et al., 2023) and RankMixer (Zhu et al., 2025), utilizing hierarchical mechanisms for efficiency. The third group represents Generative/Large-Scale Models, including HSTU (Zhai et al., 2024), MTGR (Han et al., 2025), OneTrans (Zhang et al., 2025), and HHFT (Yu et al., 2025), which are state-of-the-art architectures designed for extremely long-term history modeling.

3.2. Experimental Results

3.2.1. SOTA Comparison

For offline evaluation, all experiments were repeated 5 times on $\mathcal{D}_{\text{test}}$. For online A/B testing (following standard protocols (Kohavi et al., 2009)), models are deployed to serve 1% of live traffic. The comparative results are presented in Table 1.

Analyzing the results reveals a clear evolution in model performance. Traditional models like DNN and DCN-v2 show limited GAUC as they fail to capture sequential dependencies. While DIN significantly improves accuracy by introducing attention mechanisms, it inadvertently exacerbates redundancy because it explicitly attends to the purchased item if the candidate is similar. Modern SOTA sequence models (e.g., MTGR, OneTrans) achieve the highest GAUC scores, proving their ability to capture long-term interests; however, their high PPRR indicates a critical flaw—they treat post-purchase signals merely as “strong positive feedback,” leading to severe post-purchase redundancy.

In contrast, our SAM framework achieves a significant improvements across all metrics. It statistically ties with or surpasses OneTrans in AUC and GAUC, while crucially reducing the PPRR by over 60% compared to the strongest baseline. This confirms that SAM correctly “exits” satisfied interests without compromising the prediction accuracy for other relevant items. Online A/B testing further validates this impact, showing a +1.1% lift in CTR and a +0.9% lift in GMV, driven by the effective reduction of redundant exposures which allows users to explore new categories. Furthermore, a quantitative breakdown confirms that SAM successfully captures distinct product lifecycles: it predicts extended satiation cycles averaging over 300 days for typical durables (e.g., refrigerators), while correctly inferring much shorter rhythms (~15–30 days) for high-frequency consumables (e.g., tissues). By learning these personalized cycles rather than relying on a rigid heuristic baseline (e.g., DIN + Fixed-Window Filter, which severely degrades GAUC to 0.670 and drops online GMV by 0.3% due to indiscriminate over-suppression), SAM dynamically balances redundancy mitigation with legitimate repurchase demands.

3.2.2. Ablation Study

To validate the contribution of each component, we conduct an ablation study shown in Table 3. The observed order of contribution to GAUC and Redundancy reduction is Dual-path Retrieval ζ TTNP ζ ASGU Gating. Specifically, removing the rhythm retrieval module causes a slight drop in GAUC but a sharp increase in PPRR, confirming that historical purchase rhythm is the primary signal for determining “when to stop.” Furthermore, without the auxiliary TTNP loss, the model

fails to learn the diverse satiation cycles of different goods (e.g., distinguishing refrigerators from tissues), leading to sub-optimal GAUC. Finally, replacing the adaptive ASGU with a hard mask maintains low redundancy but hurts GAUC, as it mistakenly suppresses "lead-in" interests such as pre-repurchase browsing.

Table 3. Ablation outcomes on SAM variants. GAUC is the primary accuracy metric.

Variant	GAUC (↑) PPRR (↓)	
Full SAM	0.691	4.1%
w/o TTNP Task	0.688 (↓)	8.4% (↑)
w/o Dual-path Retrieval	0.682 (↓)	12.9% (↑↑)
w/o ASGU (Hard Mask)	0.685 (↓)	4.0% (≈)

4. Conclusion

In this paper, we propose the Satiation-Aware Mechanism (SAM), a novel framework to address the post-purchase redundancy problem in industrial fine-ranking systems. By introducing a Dual-path Context Retrieval module and an adaptive gating unit supervised by a Time-to-Next-Purchase (TTNP) task, SAM effectively models the "Interest Exit" phenomenon. Extensive experiments on industrial datasets demonstrate that SAM significantly reduces redundancy metrics (PPRR) while maintaining state-of-the-art ranking accuracy (GAUC). Online A/B testing further validates its business value, showing substantial gains in CTR and GMV. These findings highlight the importance of explicitly modeling intent termination in long-sequence user behavior learning.

5. Acknowledgments

We acknowledge the Alibaba PAI Team for releasing TorchEasyRec(*Team*, [2024](#)), which supported the engineering implementation and large-scale training of our experiments.

References

- J. Carbonell and J. Goldstein (1998) The use of MMR, diversity-based reranking for reordering documents and producing summaries. In Proceedings of the 21st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 335–336. Cited by: [§1](#), [§3.1.2](#).
- H. Cheng, L. Koc, J. Harmsen, T. Shaked, T. Chandra, H. Aradhye, G. Anderson, G. Corrado, W. Chai, M. Ispir, et al. (2016) Wide & deep learning for recommender systems. In Proceedings of the 1st Workshop on Deep Learning for Recommender Systems, pp. 7–10. Cited by: [§3.1.3](#).
- P. Covington, J. Adams, and E. Sargin (2016) Deep neural networks for youtube recommendations. In Proceedings of the 10th ACM Conference on Recommender Systems, pp. 191–198. Cited by: [§3.1.3](#).

- N. Du, H. Dai, R. Trivedi, U. Upadhyay, M. Gomez–Rodriguez, and L. Song (2016) Recurrent marked temporal point processes: embedding event history to vector. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1555–1564. Cited by: [§1](#).
- H. Gui, R. Wang, K. Yin, L. Jin, M. Kula, T. Xu, L. Hong, and E. H. Chi (2023) Hiformer: heterogeneous feature interactions learning with transformers for recommender systems. arXiv preprint arXiv:2311.05884. Cited by: [Table 1](#), [§3.1.3](#).
- R. Han, B. Yin, S. Chen, H. Jiang, F. Jiang, X. Li, C. Ma, M. Huang, X. Li, C. Jing, Y. Han, M. Zhou, L. Yu, C. Liu, and W. Lin (2025) MTGR: industrial–scale generative recommendation framework in meituan. arXiv preprint arXiv:2505.18654. Cited by: [Table 1](#), [§3.1.3](#).
- W. Kang and J. McAuley (2018) Self–attentive sequential recommendation. In 2018 IEEE International Conference on Data Mining (ICDM), pp. 197–206. Cited by: [§1](#).
- R. Kohavi, R. Longbotham, D. Sommerfield, and R. M. Henne (2009) Controlled experiments on the web: survey and practical guide. Data Mining and Knowledge Discovery 18 (1), pp. 140–181. Cited by: [§3.2.1](#).
- A. Kulesza and B. Taskar (2012) Determinantal point processes for machine learning. Foundations and Trends in Machine Learning 5 (2–3), pp. 123–286. Cited by: [§1](#), [§3.1.2](#).
- J. Li, Y. Wang, and J. McAuley (2020) Time interval aware self–attention for sequential recommendation. In Proceedings of the 13th International Conference on Web Search and Data Mining, pp. 322–330. Cited by: [§1](#).
- H. Mei and J. M. Eisner (2017) The neural hawkes process: a neurally self–modulating multivariate point process. Advances in Neural Information Processing Systems 30. Cited by: [§1](#).
- P. Ren, Z. Chen, J. Li, Z. Ren, J. Ma, and M. de Rijke (2019) RepeatNet: a repeat aware neural recommendation machine for session–based recommendation. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33, pp. 4806–4813. Cited by: [§1](#).
- F. Sun, J. Liu, J. Wu, C. Pei, X. Lin, W. Ou, and P. Jiang (2019) BERT4Rec: sequential recommendation with bidirectional encoder representations from transformer. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management, pp. 1441–1450. Cited by: [§1](#).
- A. P. Team (2024) TorchEasyRec: an easy–to–use framework for recommendation. Note: <https://github.com/alibaba/TorchEasyRec> Cited by: [§5](#).
- A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin (2017) Attention is all you need. Advances in Neural Information Processing Systems 30. Cited by: [§1](#).
- R. Wang, R. Shivanna, D. Z. Cheng, S. Jain, D. Lin, L. Hong, and E. H. Chi (2021) DCN V2: improved deep & cross network and practical lessons for web–scale learning to rank systems. In Proceedings of the Web Conference 2021, pp. 1785–1797. Cited by: [Table 1](#), [§3.1.3](#).
- L. Yu, W. Zhang, S. Zhou, T. Zhang, Z. Zhang, and D. Ou (2025) HHFT: hierarchical heterogeneous feature transformer for recommendation systems. arXiv preprint arXiv:2511.20235. Cited by: [Table 1](#), [§3.1.3](#).
- J. Zhai, L. Liao, X. Liu, Y. Wang, R. Li, X. Cao, L. Gao, Z. Gong, F. Gu, M. He, Y. Lu, and Y. Shi (2024) Actions speak louder than words: trillion–parameter sequential transducers for

- generative recommendations. arXiv preprint arXiv:2402.17152. Cited by: [Table 1](#), [§3.1.3](#).
- Z. Zhang, H. Pei, J. Guo, T. Wang, Y. Feng, H. Sun, S. Liu, and A. Sun (2025) OneTrans: unified feature interaction and sequence modeling with one transformer in industrial recommender. arXiv preprint arXiv:2510.26104. Cited by: [Table 1](#), [§3.1.3](#).
 - G. Zhou, N. Mou, Y. Fan, Q. Pi, W. Bian, C. Zhou, X. Zhu, and K. Gai (2019) Deep interest evolution network for click-through rate prediction. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 33, pp. 5941–5948. Cited by: [§1](#).
 - G. Zhou, X. Zhu, C. Song, K. Gai, Y. Fan, H. Zhu, X. Ma, Y. Yan, J. Jin, and H. Li (2018) Deep interest network for click-through rate prediction. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 1059–1068. Cited by: [§1](#), [Table 1](#), [§3.1.2](#), [§3.1.3](#).
 - J. Zhu, Z. Fan, X. Zhu, Y. Jiang, H. Wang, X. Han, H. Ding, X. Wang, W. Zhao, Z. Gong, H. Yang, Z. Chai, Z. Chen, Y. Zheng, Q. Chen, F. Zhang, X. Zhou, P. Xu, X. Yang, D. Wu, and Z. Liu (2025) RankMixer: scaling up ranking models in industrial recommenders. arXiv preprint arXiv:2507.15551. Cited by: [Table 1](#), [§3.1.3](#).

Experimental support, please [view the build logs](#) for errors. Generated by [L^AT_EX](#) .

Instructions for reporting errors

We are continuing to improve HTML versions of papers, and your feedback helps enhance accessibility and mobile support. To report errors in the HTML that will help us improve conversion and rendering, choose any of the methods listed below:

- Click the "Report Issue" () button, located in the page header.

Tip: You can select the relevant text first, to include it in your report.

Our team has already identified [the following issues](#). We appreciate your time reviewing and reporting rendering errors we may not have found yet. Your efforts will help us improve the HTML versions for all readers, because disability should not be a barrier to accessing research. Thank you for your continued support in championing open access for all.

Have a free development cycle? Help support accessibility at arXiv! Our collaborators at LaTeXML maintain a [list of packages that need conversion](#), and welcome [developer contributions](#).

We gratefully acknowledge support from our **major funders**, [member institutions](#), and all contributors.

[About](#) · [Help](#) · [Contact](#) · [Subscribe](#) · [Copyright](#) · [Privacy](#) · [Accessibility](#) · [Operational Status](#) ([opens in new tab](#)).

Major funding support from

 [Simons Foundation](#)  [Simons Foundation International](#)  [Schmidt Sciences](#)

