



# Modeling Temporal Positive and Negative Excitation for Sequential Recommendation

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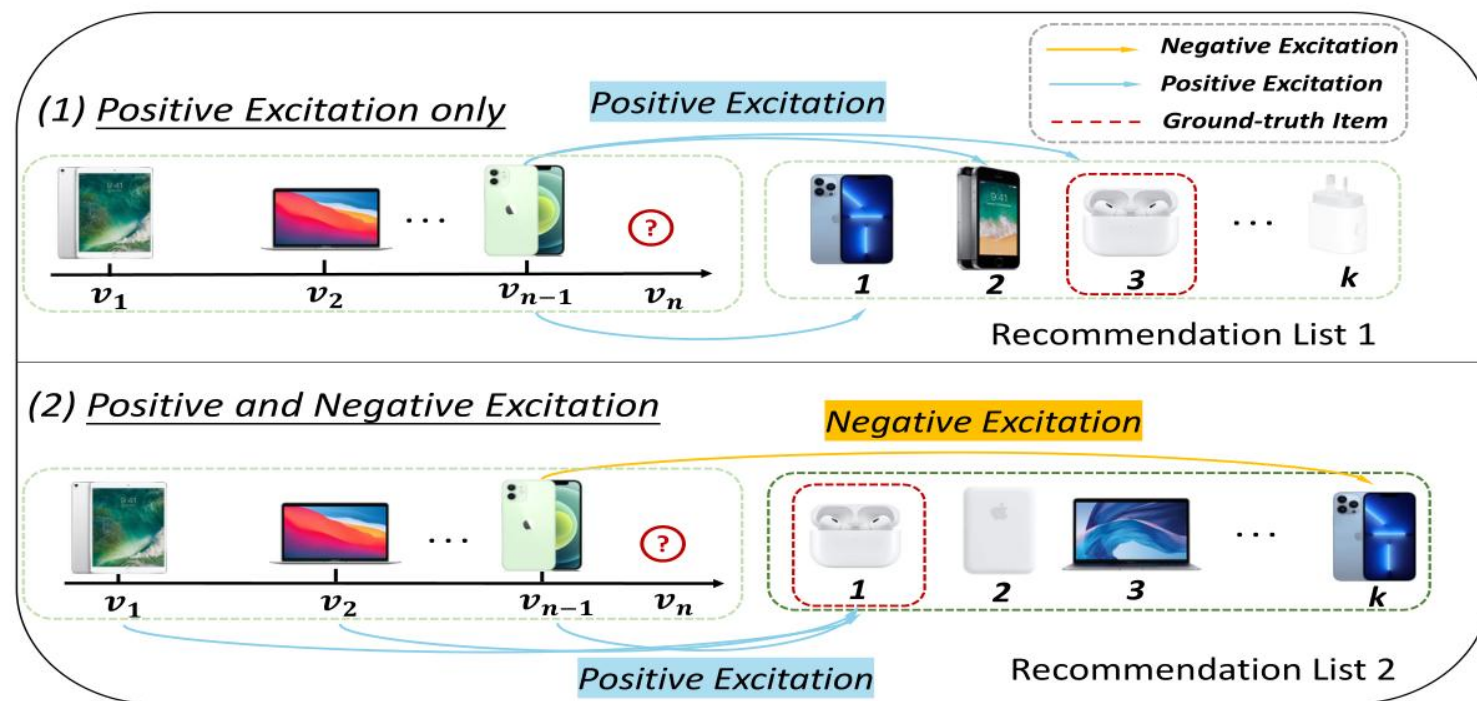
CSIRO's Data 61 and UNSW  
Sydney, NSW, Australia

code:None

WWW 2023



# Introduction



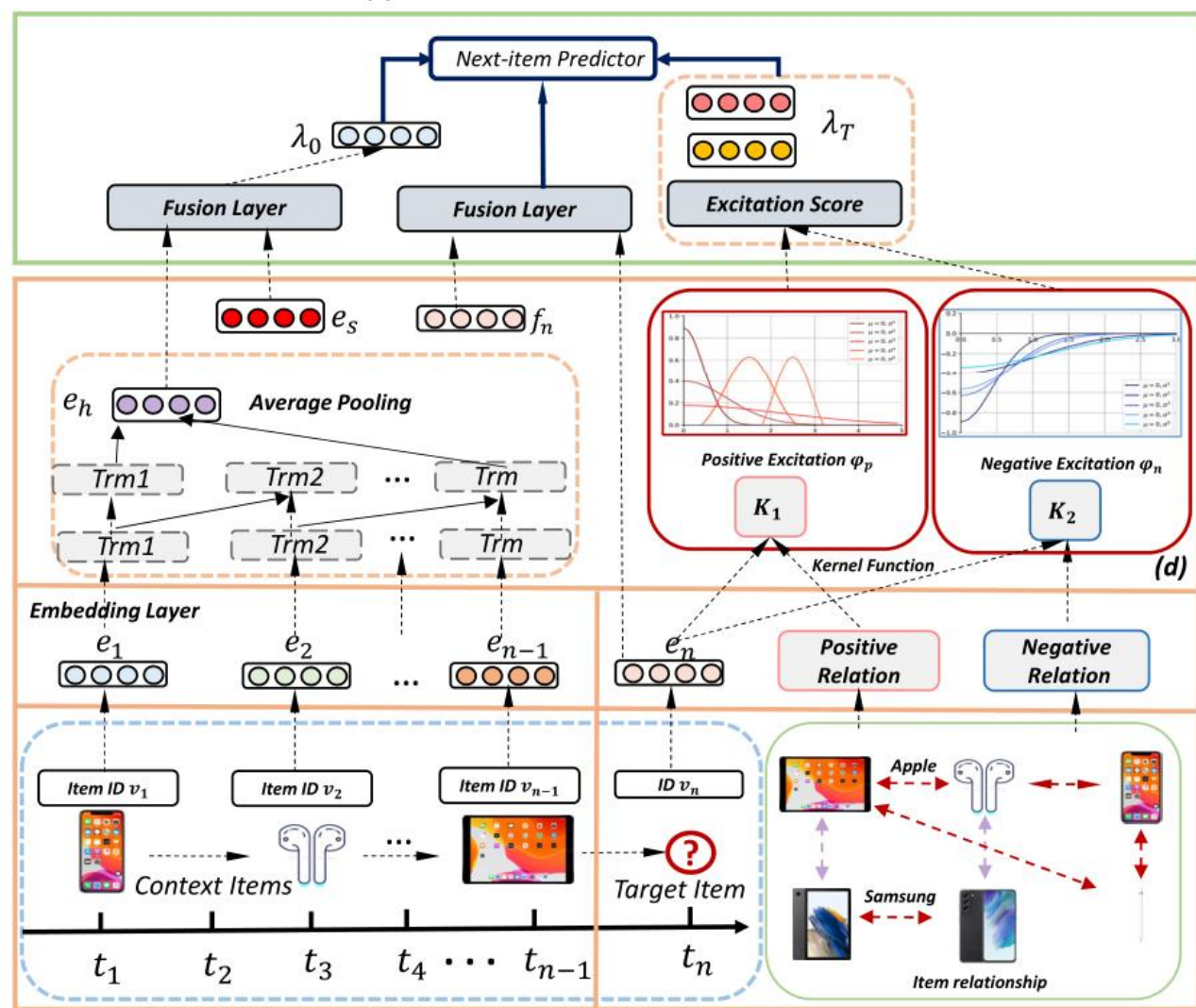
Most of the existing SRSs only model users' dynamic interest in items while overlooking users' static interest.

Most of the existing SRSs cannot thoroughly capture users' dynamic interest since they often only model the positive excitation while overlooking negative one.

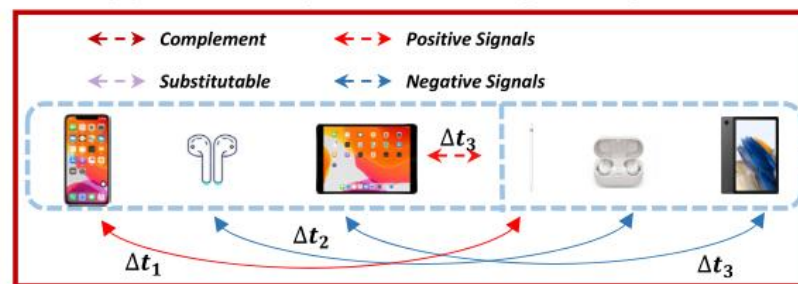
**Figure 1: An example of recommendations via modeling positive excitation only (existing methods) and modeling both positive and negative excitation (our proposal). Clearly, the latter achieves better performance via ranking the ground-truth next item AirPods at the Top-1 position in the recommendation list.**

# Method

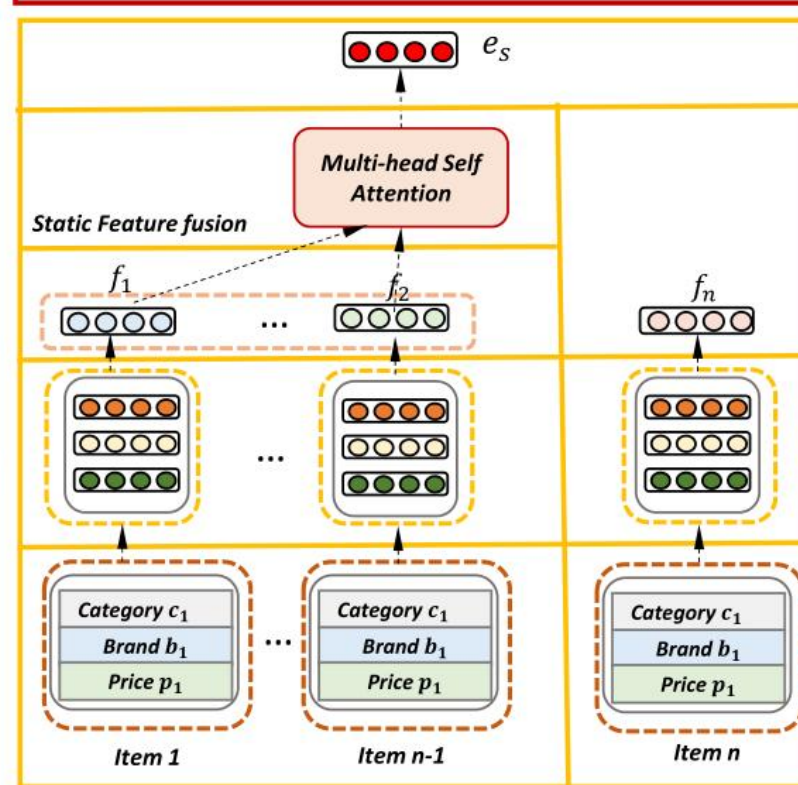
(c) Next-item Prediction Module



(d) Illustration of Positive and Negative Signals



Four explicit relations:  
also\_buy (1),  
also\_view (2),  
share\_brand (3),  
similar\_item (4).

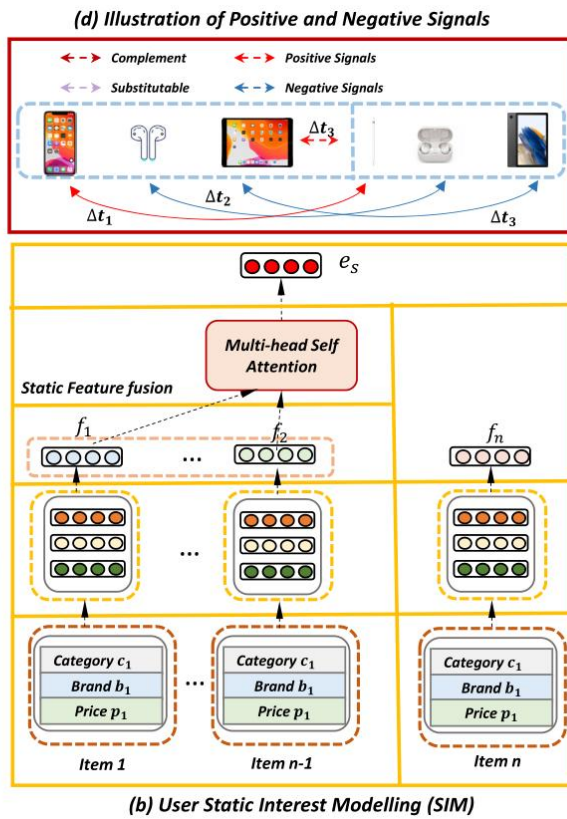
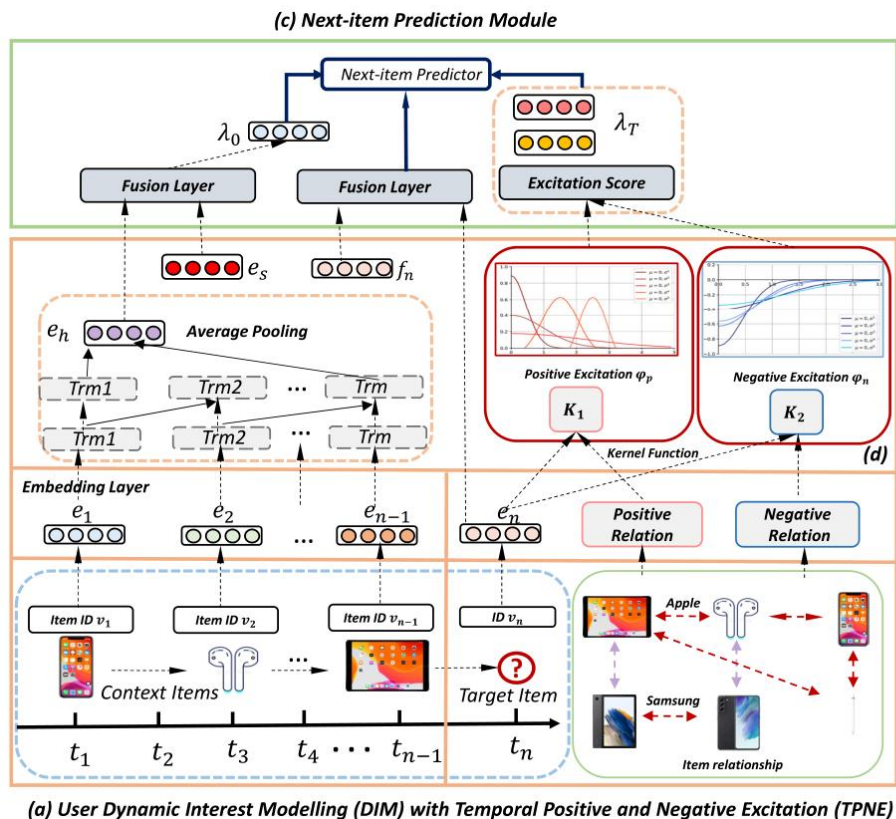


(a) User Dynamic Interest Modelling (DIM) with Temporal Positive and Negative Excitation (TPNE)

(b) User Static Interest Modelling (SIM)

Figure 2: The framework of our proposed SDIL framework.

# Method



$$\lambda(t) = \mu(t) + \sum_{t_i < t} \varphi(t - t_i) \quad (1)$$

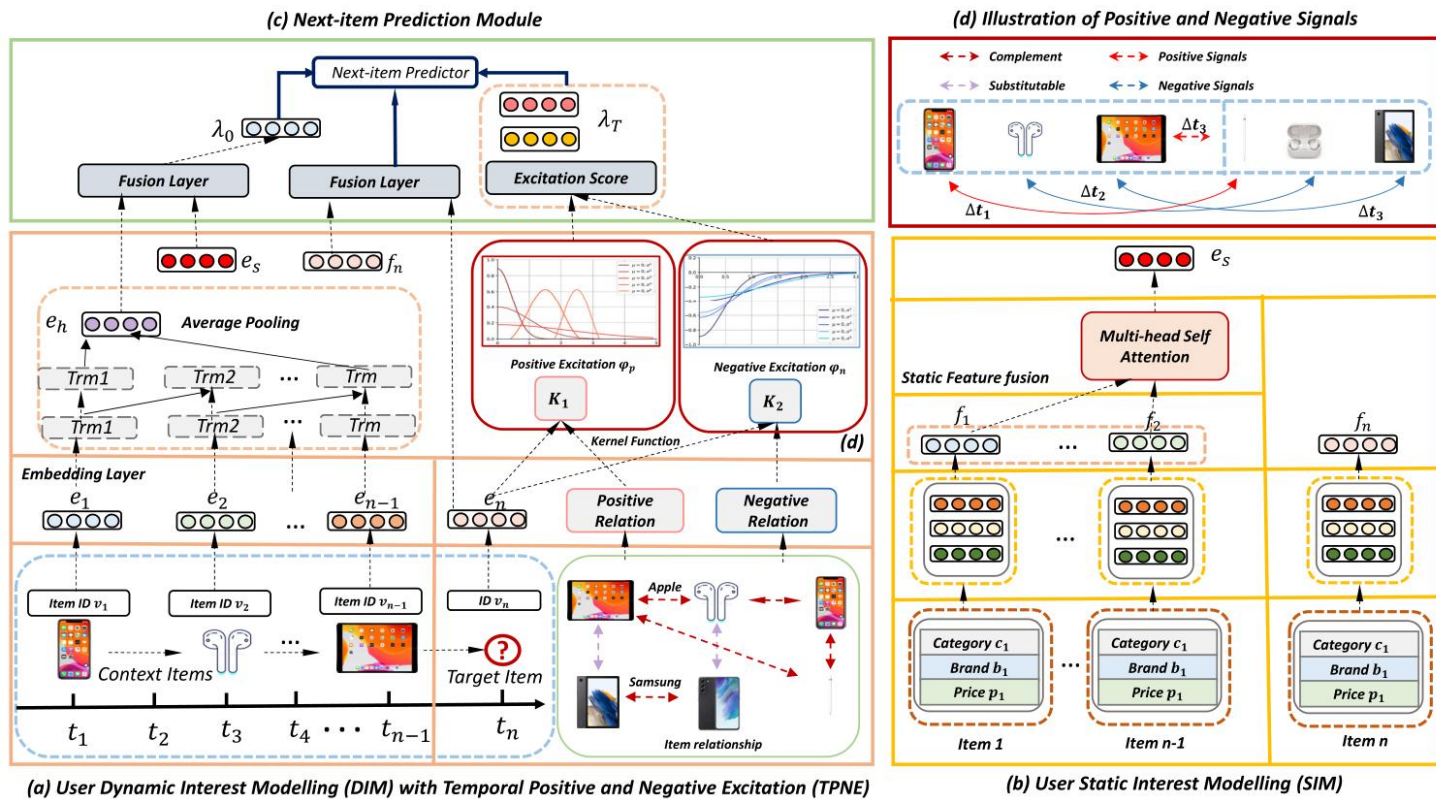
$$\lambda_T(t) = \lambda_0 + \sum_{i: t_i < t_n} \varphi(t_n - t_i) \quad (2)$$

$$\lambda_0 = e_h^T e_{v_n} + u_b + i_b \quad (3)$$

$$A_i = \text{Att}((E(H_u) + \text{POS}_i)W^Q, (E(H_u) + \text{POS}_i)W^K, (E(H_u) + \text{POS}_i)W^V) \quad (4)$$

$$\text{Att}_i = \text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \quad (5)$$

# Method



$$E(H_u) = \text{LayerNorm}(H_u + \text{Dropout}(\text{FFN}(A_i))) \quad (6)$$

$$e_h = \frac{1}{|N| - 1} \sum_{i=1}^{n-1} E(H_u)_i \quad (7)$$

$$\lambda_T(t) = \lambda_0 + \sum_{i:t_i < t_n} \varphi_p(t_n - t_i) - \sum_{j:t_j < t_n} \varphi_n(t_n - t_j) \quad (8)$$

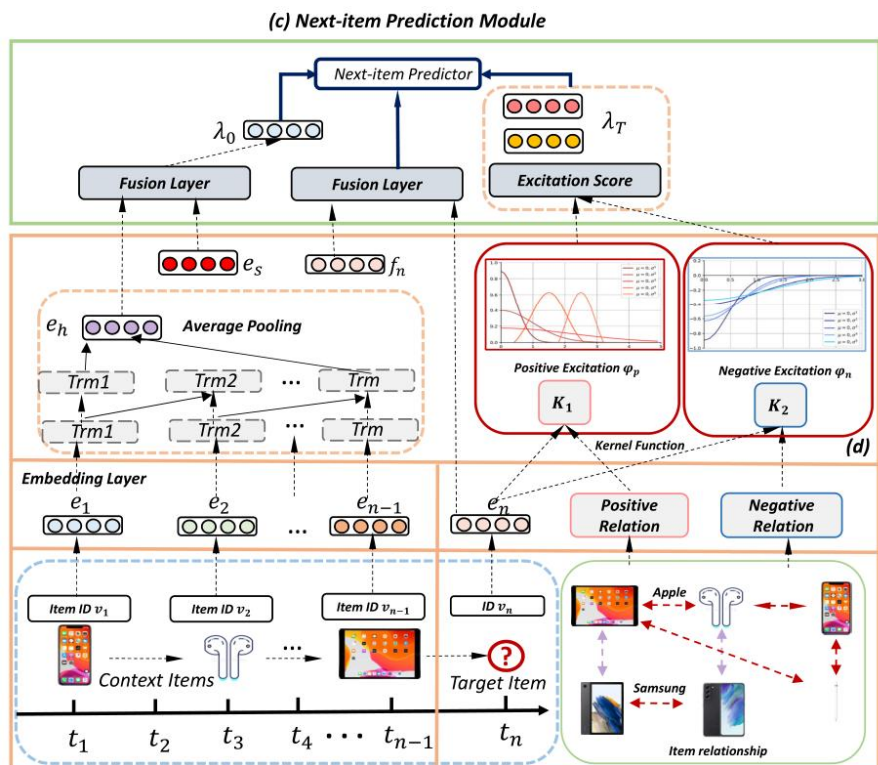
$$\varphi_p(t_n - t_i) = \sum_{i:t_i < t} I_{rp}(v_i, v_n) \mathcal{K}_1(t_n - t_i) \quad (9)$$

$$\mathcal{K}_1^i(\Delta t_1) = N(\Delta t_1 | 0, \sigma_1^v) + N(\Delta t_1 | \mu_2^v, \sigma_2^v) \quad (10)$$

$$\varphi_n(t_n - t_j) = \sum_{j:t_j < t_n} I_{rn}(v_j, v_n) \mathcal{K}_2(t_n - t_j) \quad (11)$$

$$\mathcal{K}_2(\Delta t_2) = -N(\Delta t_2 | 0, \sigma_3^v) \quad (12)$$

# Method



$$f_i = c_i + b_i + p_i \quad (13)$$

$$H_f = \text{Att}(FW^Q, FW^K, FW^V) \quad (14)$$

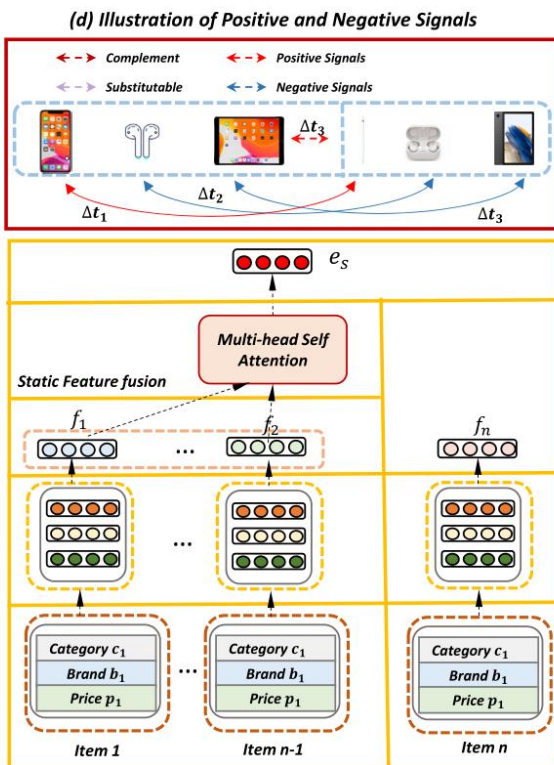
$$M_f = \text{Multihead}(F) = \text{Concat}(h_1, h_2, \dots, h_{l_f})W^O \quad (15)$$

$$h_i = \text{Att}(FW_i^Q, FW_i^K, FW_i^V) \quad (16)$$

$$M_f = \text{LayerNorm}(M_f + H_f) \quad (17)$$

$$\text{FFN}(M_f) = \text{ReLU}(M_f W_1 + b_1)W_2 + b_2 \quad (18)$$

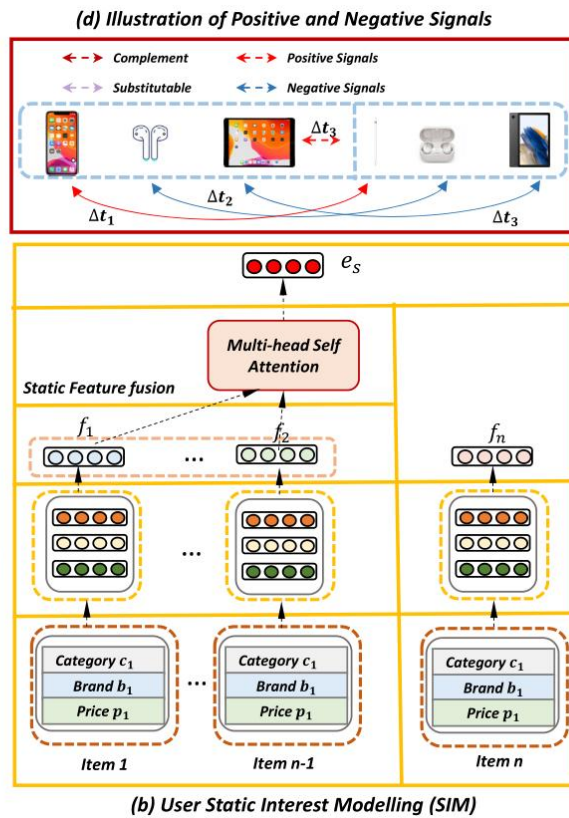
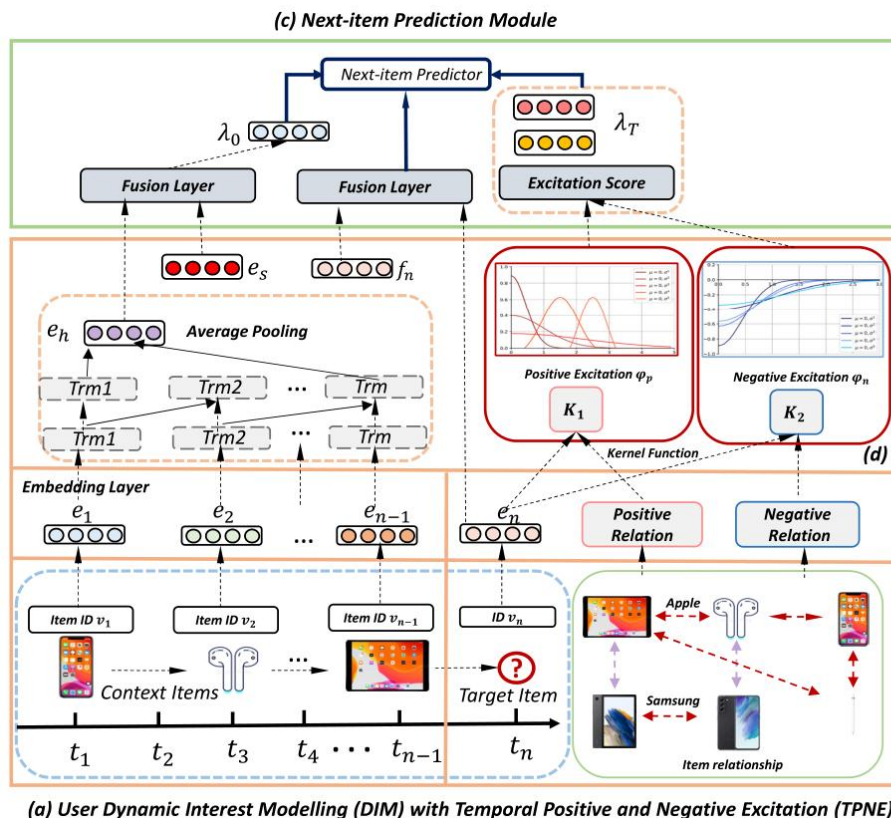
$$e_s = \frac{1}{|N| - 1} \sum_{i=1}^{|N|-1} H_f \quad (19)$$



(a) User Dynamic Interest Modelling (DIM) with Temporal Positive and Negative Excitation (TPNE)

(b) User Static Interest Modelling (SIM)

# Method



$$g = \sigma(W_1 e_s + W_2 e_h + b) \quad (20)$$

$$e_f = g \odot e_s + (1 - g) \odot e_h \quad (21)$$

$$\mathcal{L}_r = - \sum_{u \in \mathcal{U}} \sum_{i=1}^{N_u} \log \sigma(\hat{y}_{ui} - \hat{y}_{uj}) \quad (22)$$

$$\hat{y}_{ui} = e_f^T e_i + \lambda_{T,i}, \quad \hat{y}_{uj} = e_f^T e_j + \lambda_{T,j} \quad (23)$$



# Experiments

Dataset	Metric	BPR	GRU4Rec	Caser	NARM	SASRec	TiSASRec	SLRS+	Chorus	AHMP	KDA	SDIL	Improv.
Beauty	HR@5	0.3317	0.3202	0.3210	0.3334	0.3666	0.3872	0.4339	0.4536	0.4566	<u>0.4860</u>	<b>0.4926*</b>	1.36%
	HR@10	0.4355	0.4311	0.4345	0.4462	0.4590	0.4559	0.5337	0.5698	0.5519	<u>0.5997</u>	<b>0.6128*</b>	2.18%
	HR@20	0.5505	0.5693	0.5757	0.5823	0.5743	0.5700	0.6361	0.6838	0.6599	<u>0.7144</u>	<b>0.7323*</b>	2.51%
	NDCG@5	0.2361	0.2271	0.2246	0.2348	0.2797	0.2904	0.3319	0.3386	0.3496	<u>0.3648</u>	<b>0.3698*</b>	1.37%
	NDCG@10	0.2697	0.2628	0.2612	0.2712	0.3094	0.3036	0.3642	0.3762	0.3803	<u>0.4016</u>	<b>0.4088*</b>	1.79%
	NDCG@20	0.2987	0.2976	0.2967	0.3055	0.3385	0.3324	0.3900	0.4050	0.4076	<u>0.4306</u>	<b>0.4390*</b>	1.95%
	MRR	0.2363	0.2271	0.2246	0.2366	0.2923	0.2904	0.3319	0.3386	0.3421	<u>0.3549</u>	<b>0.3610*</b>	1.72%
Cellphone	HR@5	0.3387	0.3015	0.3937	0.4168	0.4439	0.4520	0.4696	0.4697	0.5045	<u>0.5497</u>	<b>0.5538*</b>	0.75%
	HR@10	0.4528	0.4301	0.5309	0.5509	0.5595	0.5767	0.5641	0.5929	0.6132	<u>0.6745</u>	<b>0.6792*</b>	0.70%
	HR@20	0.5852	0.5918	0.6810	0.6974	0.6817	0.7022	0.6637	0.7152	0.7284	<u>0.7923</u>	<b>0.8028*</b>	1.33%
	NDCG@5	0.2430	0.2085	0.2800	0.2995	0.3353	0.3344	0.3634	0.3530	0.3852	<u>0.4119</u>	<b>0.4188*</b>	1.69%
	NDCG@10	0.2798	0.2498	0.3243	0.3429	0.3727	0.3748	0.3939	0.3929	0.4204	<u>0.4523</u>	<b>0.4595*</b>	1.59%
	NDCG@20	0.3131	0.2905	0.3622	0.3799	0.4036	0.4065	0.4191	0.4238	0.4495	<u>0.4821</u>	<b>0.4908*</b>	1.80%
	MRR	0.2453	0.2271	0.2246	0.2969	0.2923	0.2904	0.3319	0.3386	0.3747	<u>0.3666</u>	<b>0.4049*</b>	10.45%
Toys	HR@5	0.2897	0.2902	0.2898	0.3173	0.3602	0.3475	0.4368	0.4124	0.4603	<u>0.4805</u>	<b>0.4953*</b>	3.08%
	HR@10	0.3897	0.4060	0.4103	0.4336	0.4570	0.4608	0.5345	0.5203	0.5587	<u>0.5882</u>	<b>0.6069*</b>	3.18%
	HR@20	0.5061	0.5546	0.5590	0.5777	0.5700	0.6003	0.6440	0.6443	0.6621	<u>0.7019</u>	<b>0.7248*</b>	3.26%
	NDCG@5	0.2068	0.1974	0.1947	0.2206	0.2738	0.2535	0.3490	0.3132	0.3600	<u>0.3660</u>	<b>0.3797*</b>	3.74%
	NDCG@10	0.2390	0.2348	0.2336	0.2581	0.3050	0.2901	0.3804	0.3480	0.3918	<u>0.4007</u>	<b>0.4157*</b>	3.74%
	NDCG@20	0.2683	0.2721	0.2710	0.2944	0.3334	0.3253	0.4081	0.3793	0.4179	<u>0.4294</u>	<b>0.4454*</b>	3.73%
	MRR	0.2116	0.2271	0.2246	0.2244	0.2923	0.2904	0.3319	0.3386	0.3547	<u>0.3666</u>	<b>0.3713*</b>	1.28%

Table 1: Overall performance.





# Experiments

**Table 2: Statistics of the datasets after preprocessing.**

Specs.	Beauty	Cellphones	Toys
# Users	22,363	27,879	19,412
# Items	12,101	10,429	11,924
# Avg. Seq Length	8.8	7.0	8.6
# Interactions	198,502	194,439	167,597
# Sparsity	99.93%	99.94%	99.93%
# Item Categories	148	20	145

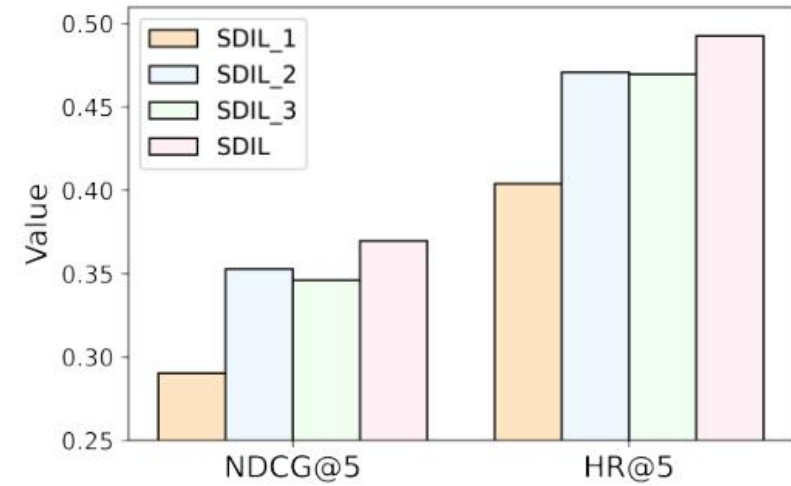


# Experiments

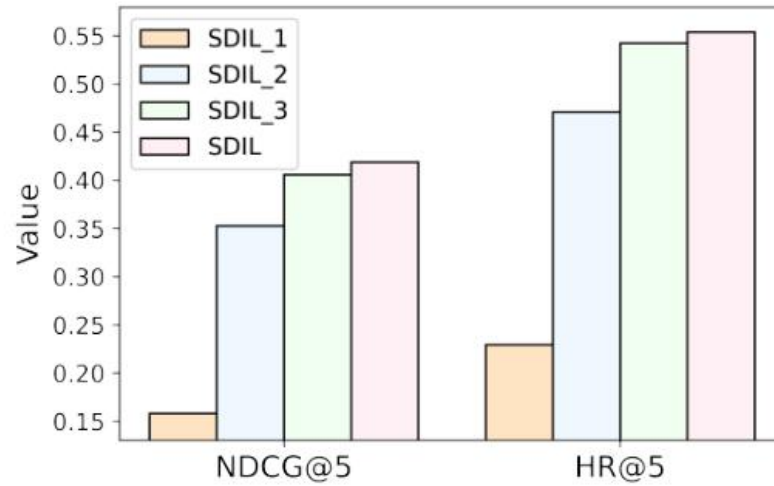
**Table 3: Performance comparison between SDIL-TPE and SDIL. \* means the improvement is significant at  $p < 0.05$ .**

Dataset	Metrics	SDIL-TPE	SDIL
Beauty	<i>HR@5</i>	0.4825	0.4926*
	<i>HR@10</i>	0.6054	0.6128*
	<i>NDCG@5</i>	0.3487	0.3698*
	<i>NDCG@10</i>	0.4014	0.4088*
	<i>MRR</i>	0.3534	0.3602*
Cellphones	<i>HR@5</i>	0.5521	0.5538*
	<i>HR@10</i>	0.6772	0.6792*
	<i>NDCG@5</i>	0.4102	0.4188*
	<i>NDCG@10</i>	0.4422	0.4595*
	<i>MRR</i>	0.4038	0.4049*
Toys	<i>HR@5</i>	0.4871	0.4953*
	<i>HR@10</i>	0.5979	0.6069*
	<i>NDCG@5</i>	0.3741	0.3797*
	<i>NDCG@10</i>	0.3670	0.4157*
	<i>MRR</i>	0.3670	0.3713*

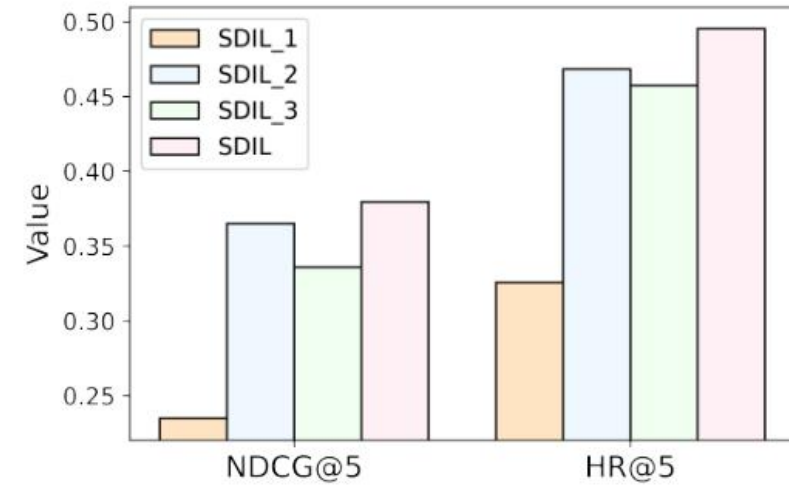
# Experiments



(a) Beauty Dataset



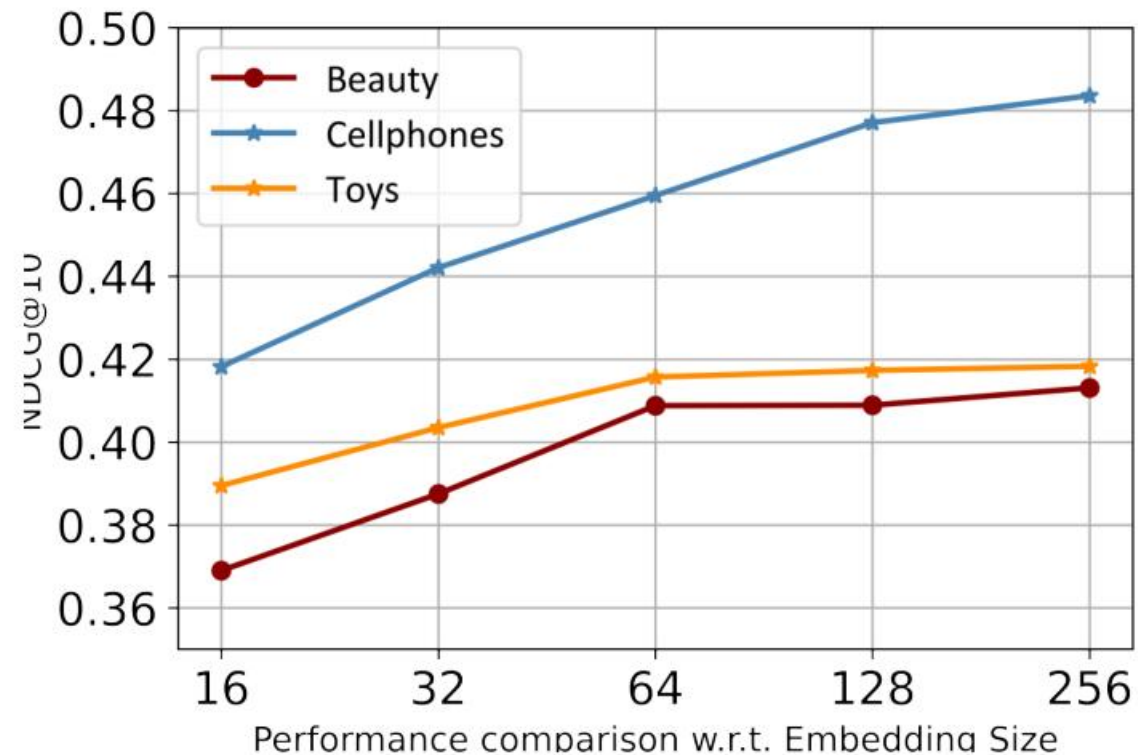
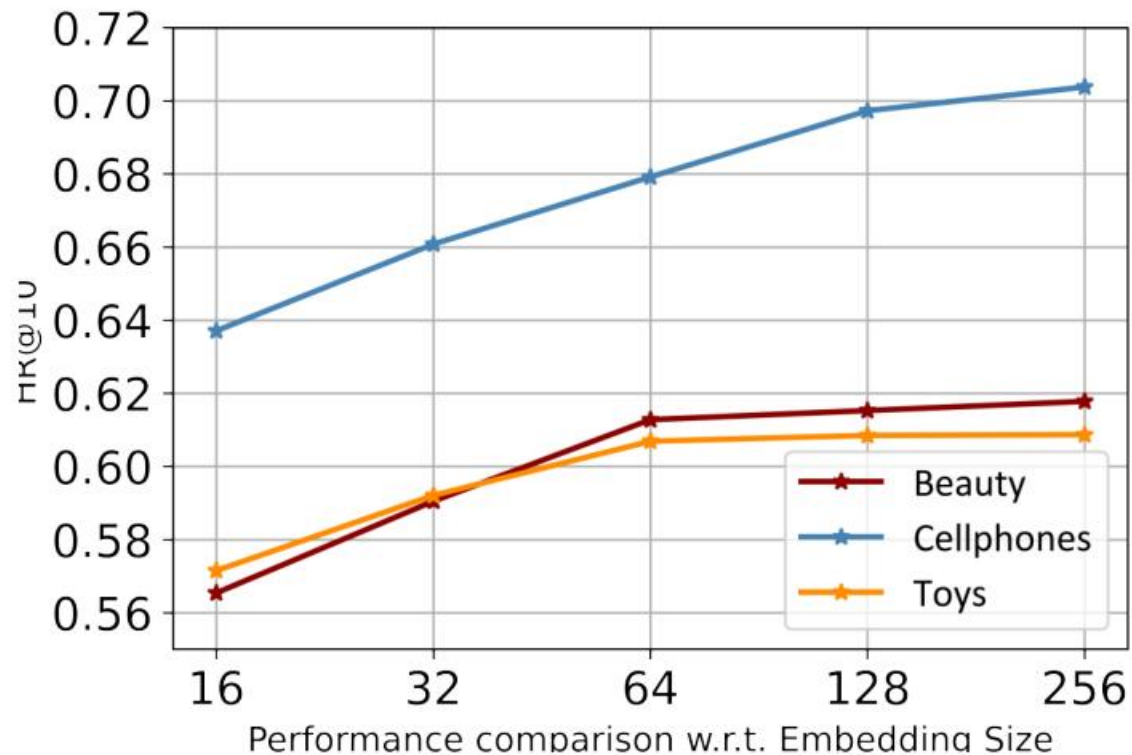
(b) Cellphones Dataset



(c) Toys Dataset

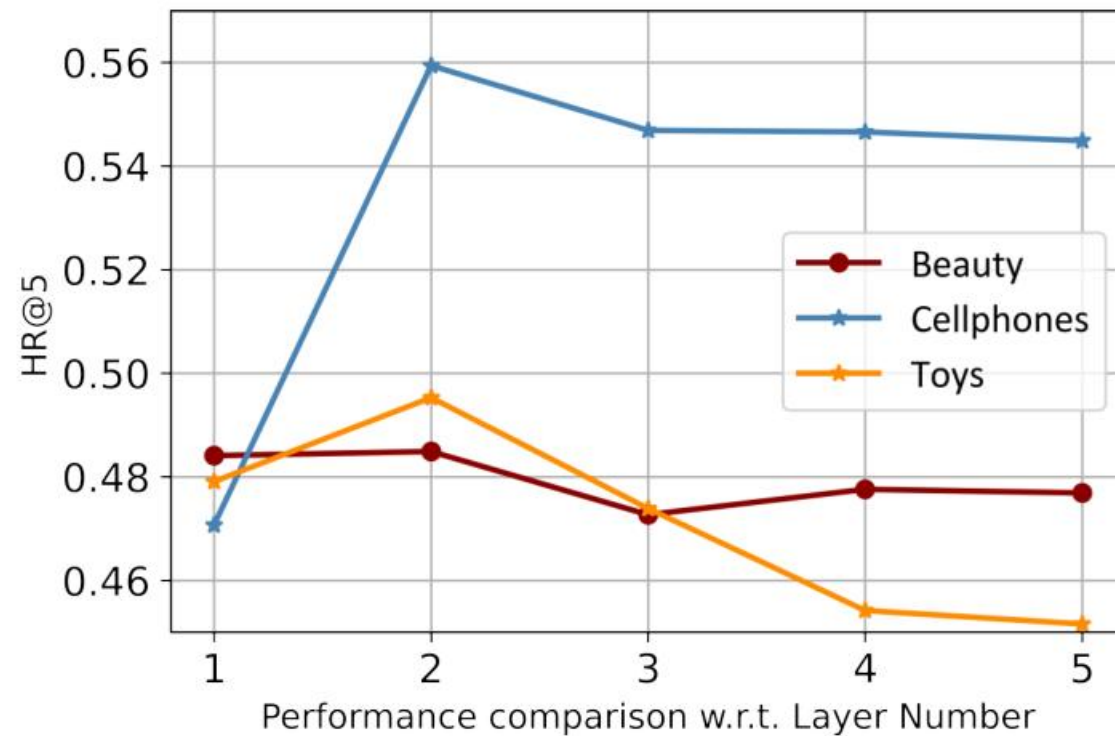
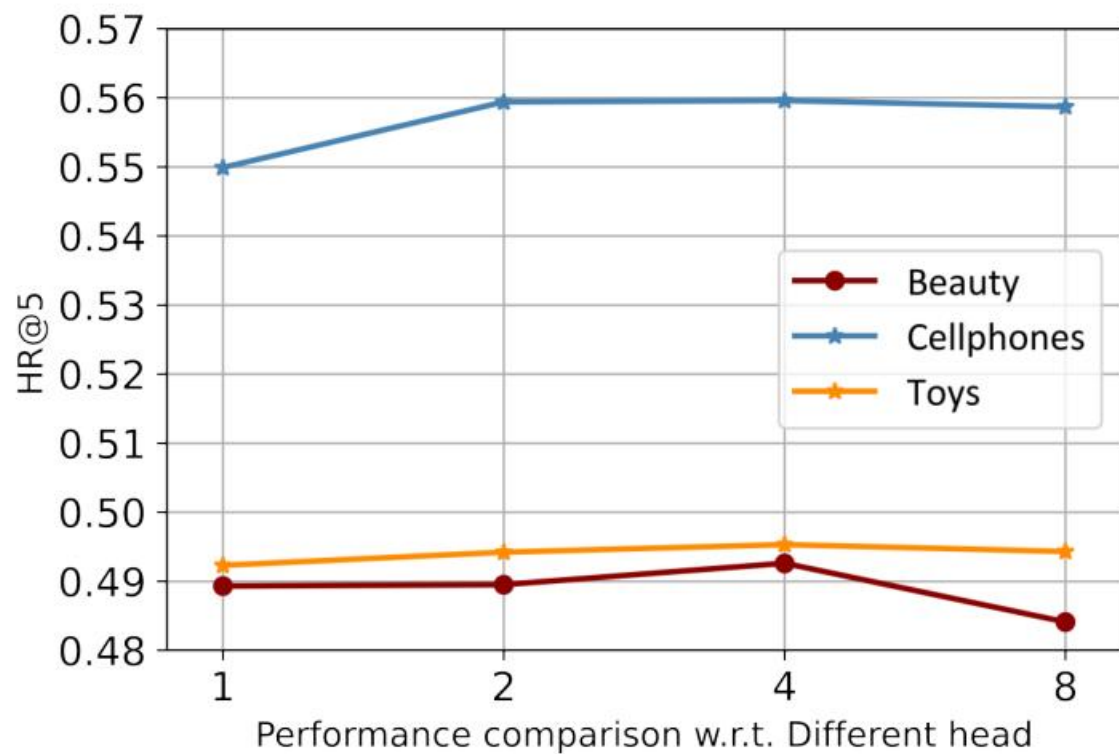
Figure 3: Ablation study on the model performance (HR@5 and NDCG@5) on different datasets.

# Experiments



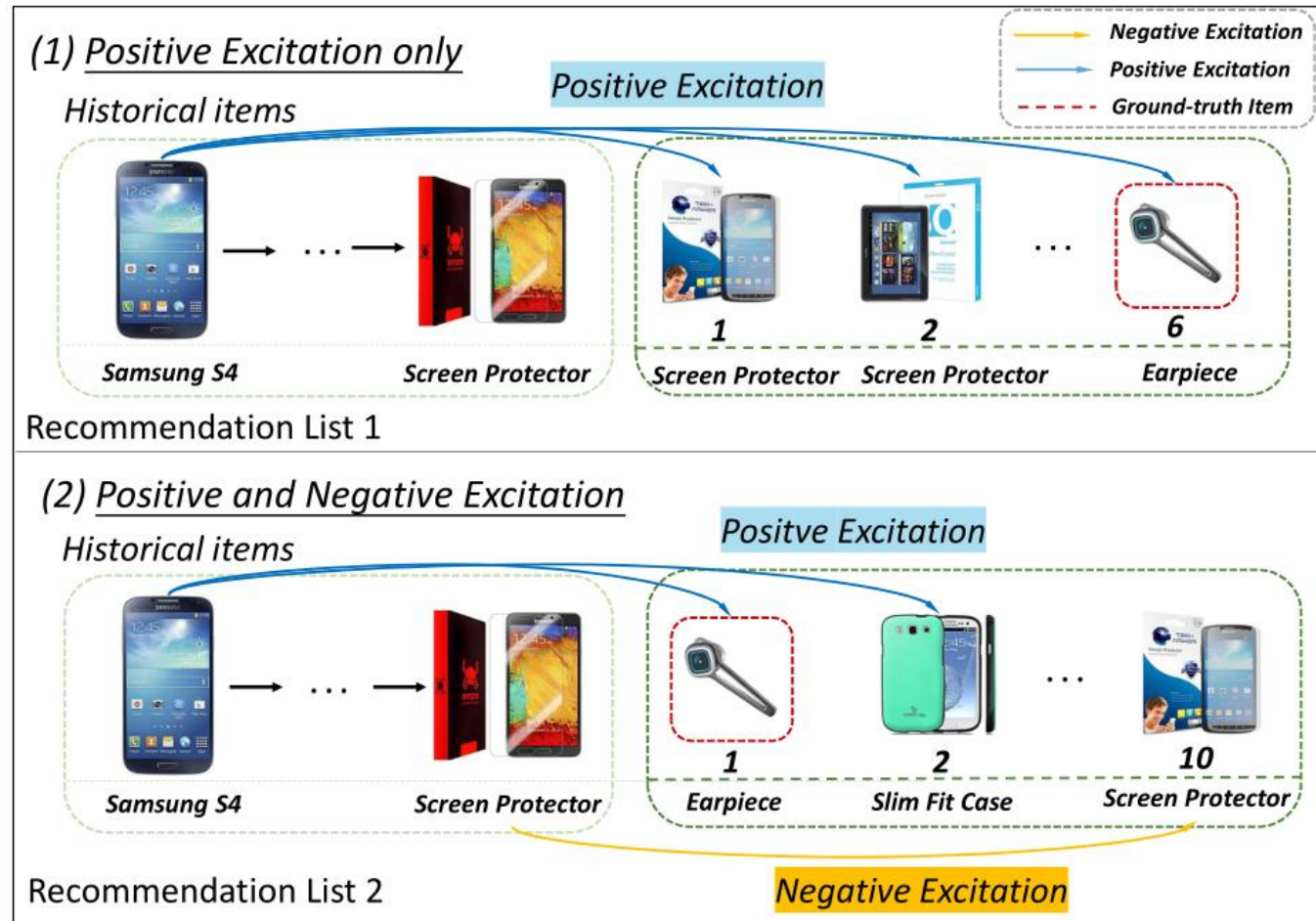
**Figure 4: Embedding size setting's effect on the model performance. (HR@5 and NDCG@10).**

# Experiments



**Figure 5: Different transformer layers setting's effect on the model performance. (HR@10 and NDCG@10).**

# Experiments



**Figure 6: Illustration of the ranking results of TPE and TPNE. The item highlighted in the red boxes is the ground-truth item.**

# Experiments







<i>Beauty Dataset</i>	<i>Ranking List Results</i>			
<i>Sampled User History Items</i>	<i>1</i>	<i>2</i>	<i>...</i>	<i>7</i>
	<p><i>Static Interest Modelling</i></p> 			
	<p><i>Dynamic Interest Modelling</i></p> 			
	<p><i>Precise Interest Modelling</i></p> 			

Figure 7: Illustration of the ranking results of SIM, DIM and DSIM. The item highlighted in the red boxes is the ground-truth item.



**Thanks**