Dual Contrastive Transformer for Hierarchical Preference Modeling in Sequential Recommendation

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Introduction

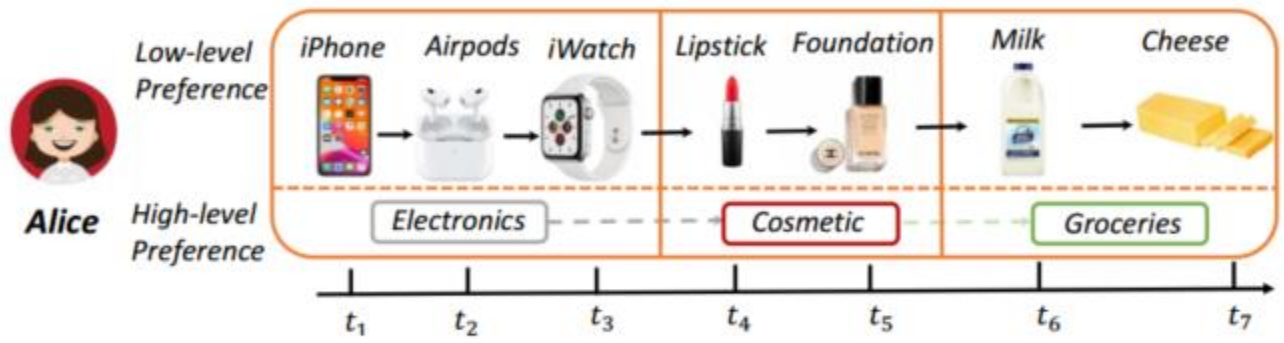


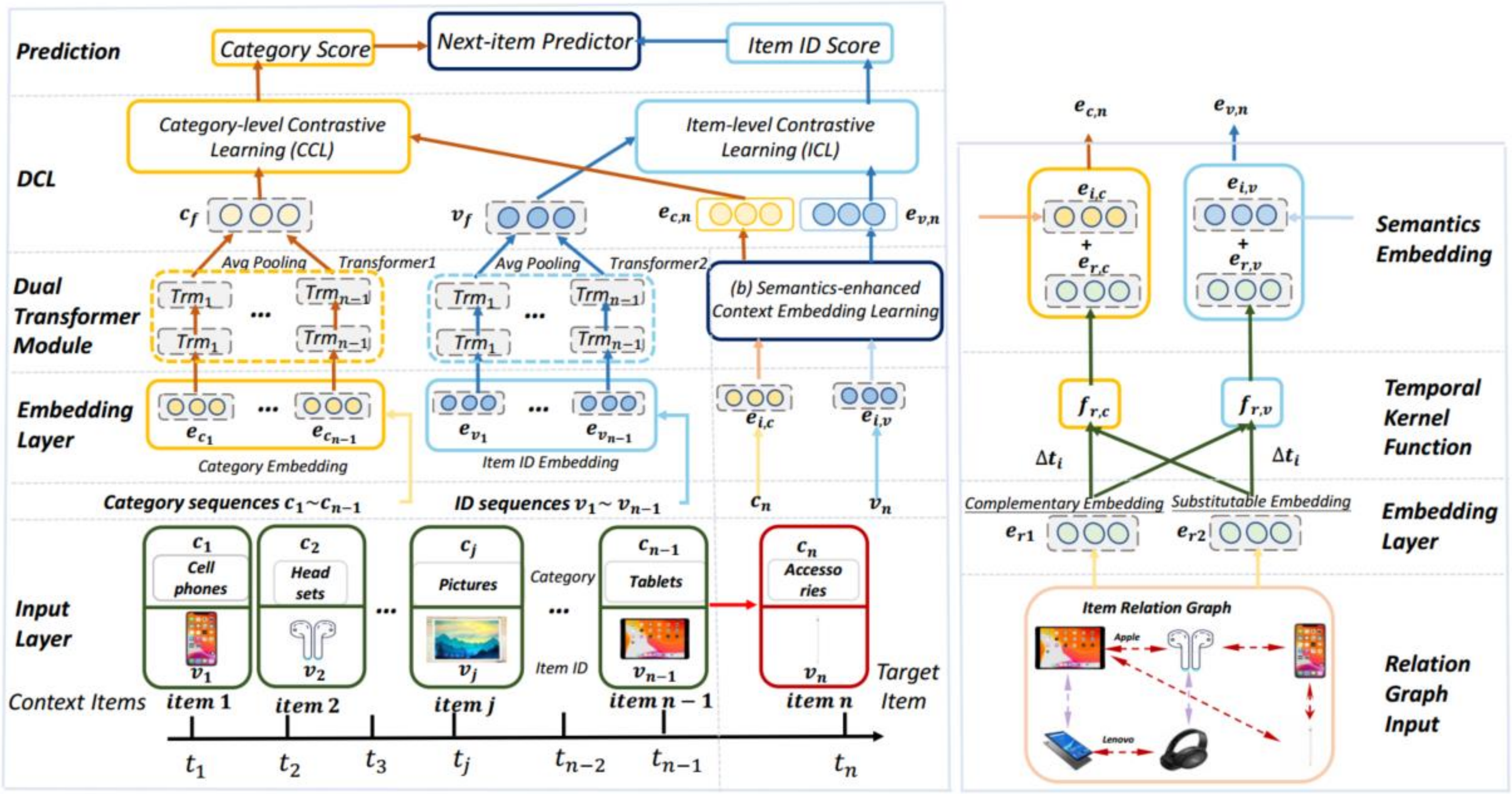
Figure 1: Alice's hierarchical preference dynamics through a sequence of purchased items. Alice's low-level preference indicated by item ID changes sharply while her high-level preference indicated by category changes smoothly.

Overlooking the informative high-level signals.

The user-item interactions in the sequential recommendation are often limited and sparse.

Contextual information is often learned from item IDs without the consideration of richer semantic relations between items,

In this paper, the author proposed a novel hierarchical preference modeling framework to substantially model the complex low- and high-level preference dynamics.



(a) The Overall Structure of Hierarchical Preference Modelling

(b) Semantics-enhanced Context Embedding Learning

PRELIMINARIES:

$$\mathcal{D} = \{\mathcal{S}_1, \ldots \mathcal{S}_i, \ldots, \mathcal{S}_n\}$$

$$\mathcal{S}_i = < \mathcal{O}_i, v_n >$$

$$\mathcal{O}_i = \{V_i, C_i, T_i\}$$

$$V_i = \{v_1, v_2, \ldots, v_{n-1}\}$$

$$C_i = \{c_1, c_2, \ldots, c_{n-1}\}$$

$$T_i = \{t_1, t_2, \ldots, t_{n-1}\}$$

Embedding Layers

Item ID Embedding:

$$E_V \in \mathbf{R}^{|V| \times d}$$

$$e_v = E_V(v_i) \in \mathbf{R}^{1xd}$$

Position Embedding:

$$E_P \in \mathbf{R}^{L \times d}$$

$$p_i = E_P(p_i) \in \mathbf{R}^{1xd}$$

Category Type Embedding:

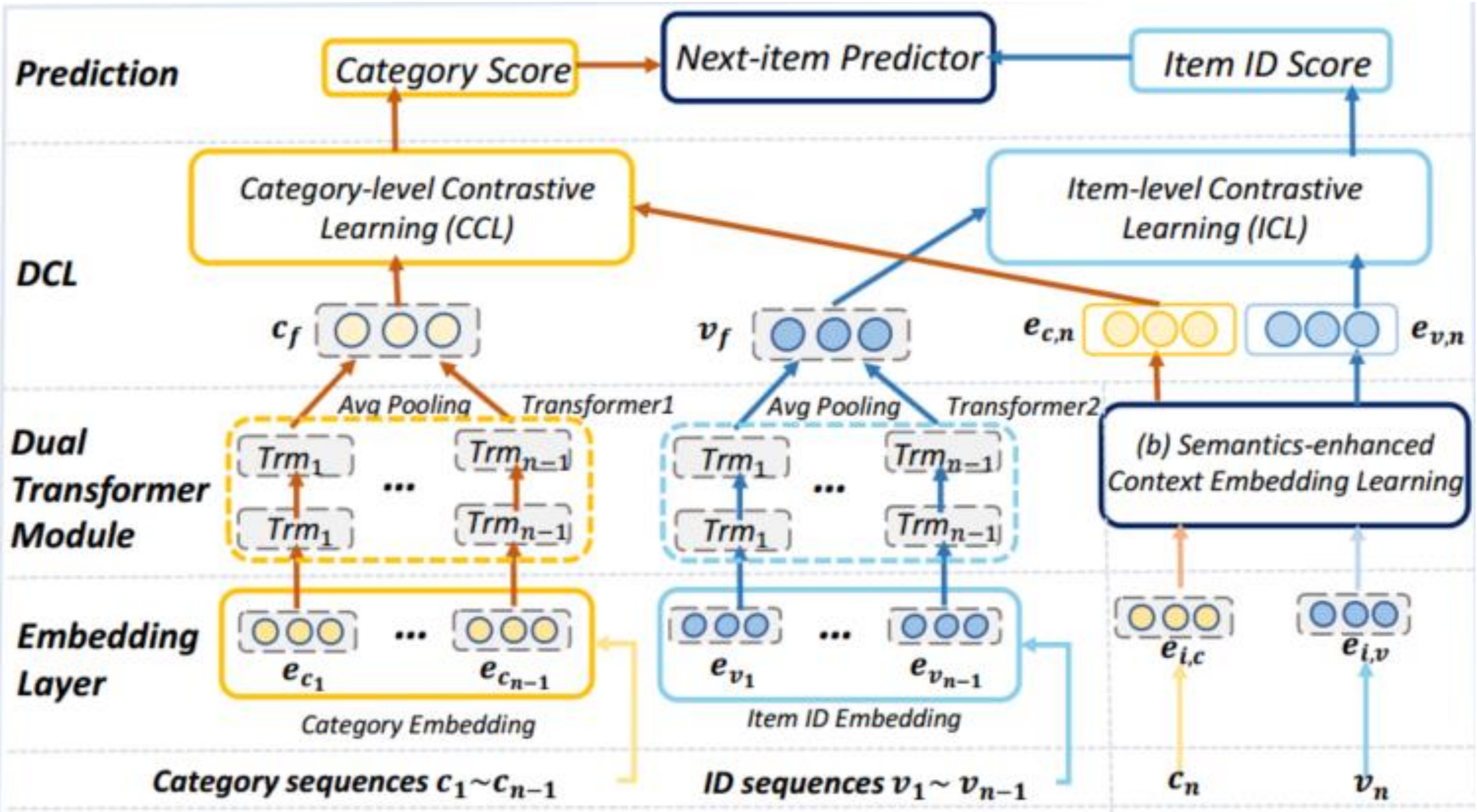
$$E_C \in \mathbf{R}^{|C| \times d}$$

$$e_c = E_C(c_i) \in \mathbf{R}^{1xd}$$

Knowledge Graph Embedding:

$$f(v_h, r, v_t) = \|\mathbf{e}_{\mathbf{v},\mathbf{h}} + \mathbf{e}_\mathbf{r} - \mathbf{e}_{\mathbf{v},\mathbf{t}}\|_2^2, \quad f(c_h, r, c_t) = \|\mathbf{e}_{\mathbf{c},\mathbf{h}} + \mathbf{e}_\mathbf{r} - \mathbf{e}_{\mathbf{c},\mathbf{t}}\|_2^2, \quad (1)$$

$e_v \in E_V$ $\quad e_r \in E_R$ $\quad e_c \in E_C$



Dual Transformer for Hierarchical Preference Modeling:

$$e_{i,v} = e_{i,v} + p_i, \quad e_{i,c} = e_{i,c} + p_i, \tag{2}$$

$$\text{MultiHead}(H_{i,*}) = W^O \text{concat}(\text{head}_1; \text{head}_2; \cdots; \text{head}_h), \tag{3}$$

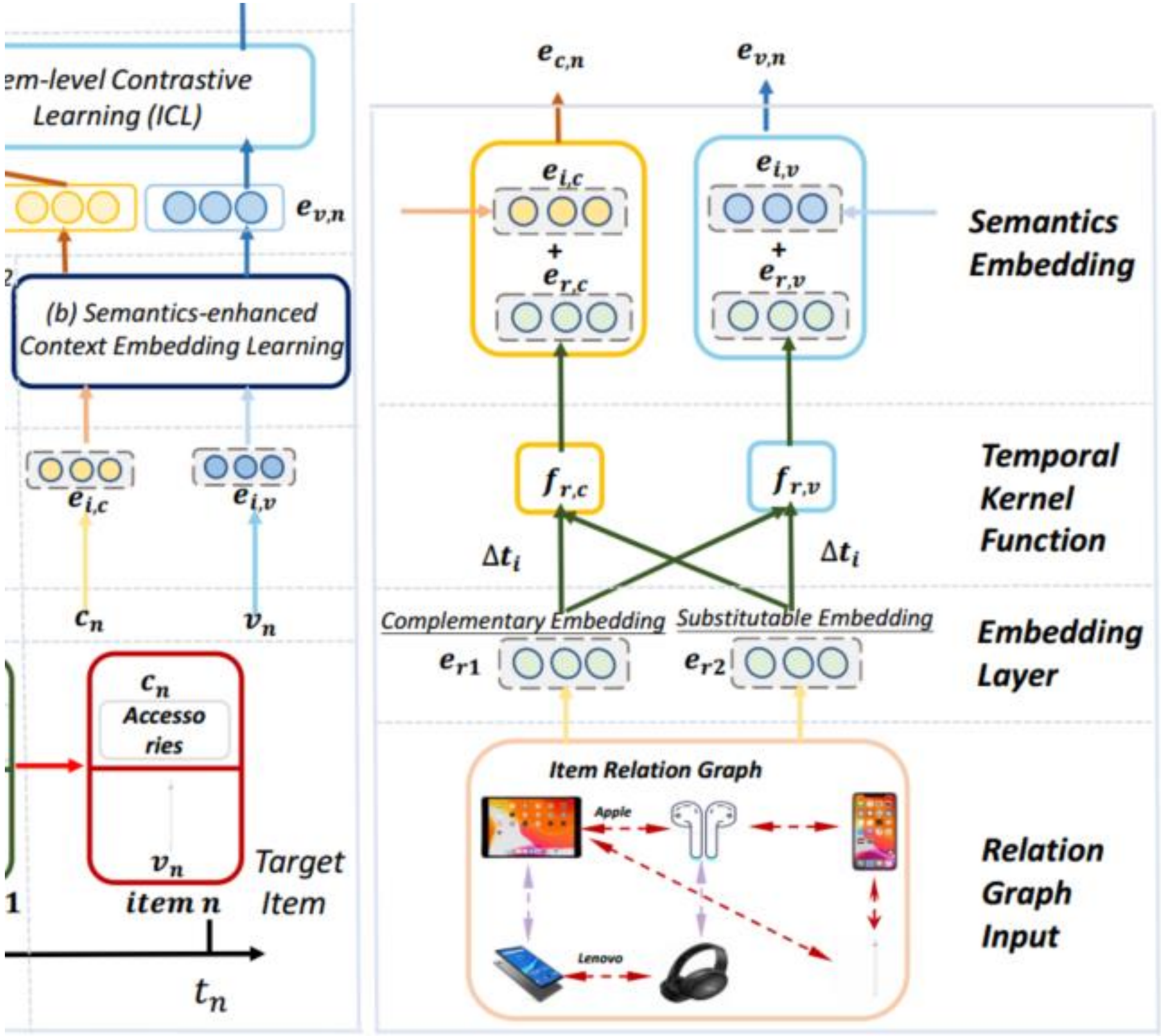
$$\text{head}_i = \text{Attention}\left(H_{i,*}W_i^Q, H_{i,*}W_i^K, H_{i,*}W_i^V\right), \tag{4}$$

$$A_i = \text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d/h}}\right)V, \tag{5}$$

$$FFN(A_i) = \text{ReLU}(A_i W_1 + b_1)W_2 + b_2, \tag{6}$$

$$H_{i,*} = LayerNorm(H_{i,*} + Dropout(FFN(A_i))), \tag{7}$$

$$v_f = \frac{1}{L}\sum_{l=1}^{L} S_{i,v_l}, \quad c_f = \frac{1}{L}\sum_{l=1}^{L} S_{i,c_l}, \tag{8}$$



Modelling

(b) Semantics-enhanced Context Embedding Learning

Semantics-enhanced Context Embedding Learning:

also_buy relations:

$$\phi_v^1(\Delta t) = N(\Delta t|0, \sigma_v), \quad \phi_c^1(\Delta t) = N(\Delta t|0, \sigma_c), \tag{9}$$

also_view relations:

$$\phi_v^2(\Delta t) = -N(\Delta t|0, \sigma_v) + N(\Delta t|\mu_v, \sigma_v), \tag{10}$$

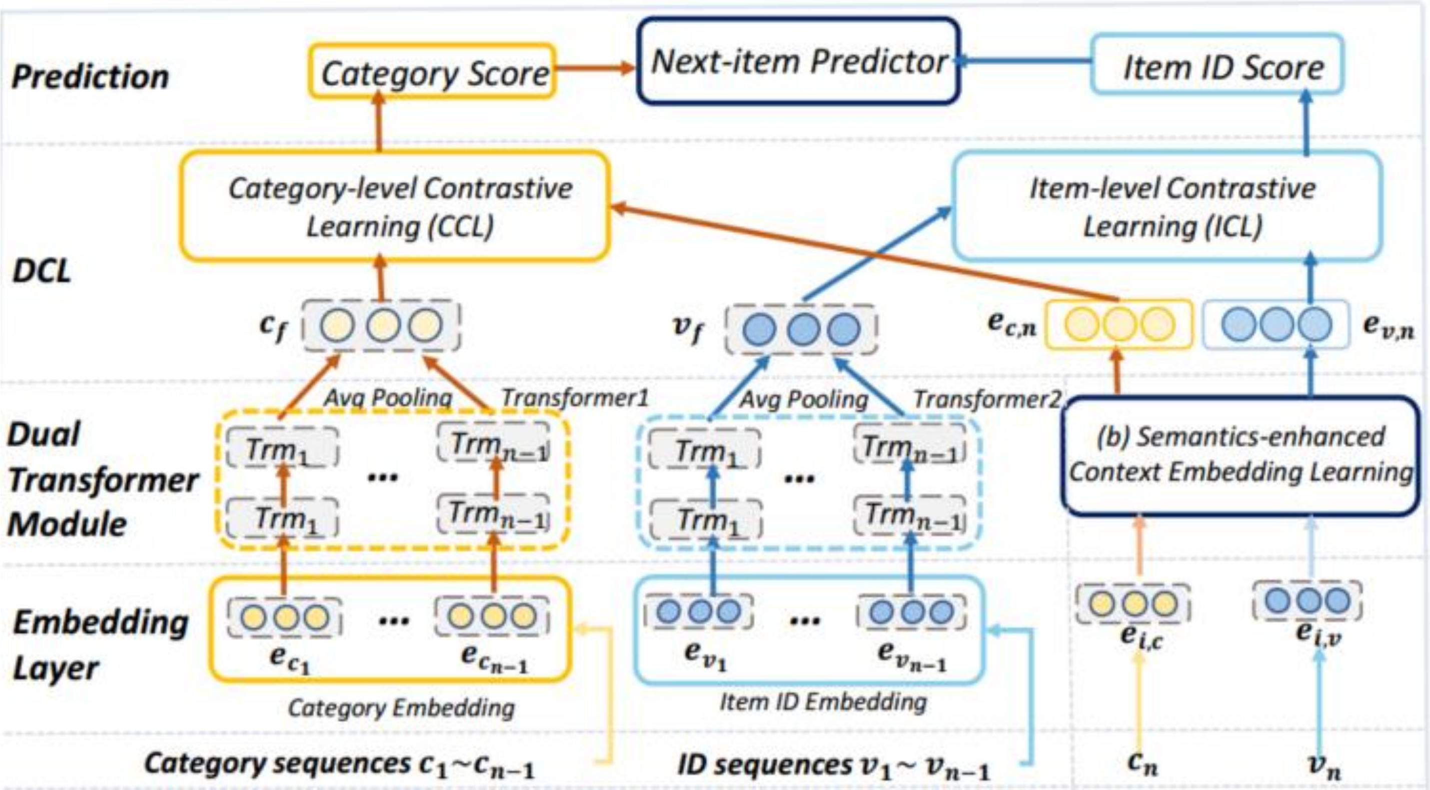
$$\phi_c^2(\Delta t) = -N(\Delta t|0, \sigma_c) + N(\Delta t|\mu_c, \sigma_c), \tag{11}$$

$$e_{v,n} = e_{v,n} + e_{r,v}, e_{r,v} = \sum_{r \in \mathcal{R}} f_r(S_{i,v}, t, e_v) \cdot e_r, \tag{12}$$

$$e_{c,n} = e_{c,n} + e_{r,c}, e_{r,c} = \sum_{r \in \mathcal{R}} f_r(S_{i,c}, t, e_i) \cdot e_r \tag{13}$$

$$f_{r1}(S_{i,v}, v, t) = \sum_{v', t'} \mathrm{I}_r(v, v') \cdot \phi(t - t'), \tag{14}$$

$$f_{r2}(S_{i,c}, c, t) = \sum_{c', t'} \mathrm{I}_r(c, c') \cdot \phi(t - t'), \tag{15}$$



$$\mathcal{L}_{cl} = \mathcal{L}_{cl_{item}} + \mathcal{L}_{cl_{cate}}. \quad (18)$$

Training and Optimization:

$$\mathcal{L}_{rec} = -\sum_{u \in \mathcal{U}} \sum_{i=1}^{N_u} \log \sigma \left(\hat{y}_{ui} - \hat{y}_{uj} \right), \quad (19)$$

$$\hat{y}_{ui} = e_{v,n}^T v_{f,i} + e_{c,n}^T c_{f,i}, \quad \hat{y}_{uj} = e_{v,n}^T v_{f,j} + e_{c,n}^T c_{f,j}, \quad (20)$$

$$\mathcal{L}_{joint} = \mathcal{L}_{rec} + \lambda \mathcal{L}_{cl}. \quad (21)$$

Semantics-enhanced Context Embedding Learning:

$$\mathcal{L}_{cl_{item}}(e_{v,n}, v_f) = -\log \frac{\exp(\text{sim}(e_{v,n}, v_f))}{\exp(\text{sim}(e_{v,n}, v_f))) + \sum_{v_f^- \in V_f} \text{sim}(e_{v,n}, v_f^-)}, \quad (16)$$

$$\mathcal{L}_{cl_{cate}}(e_{c,n}, c_f) = -\log \frac{\exp(\text{sim}(e_{c,n}, c_f))}{\exp(\text{sim}(e_{c,n}, c_f))) + \sum_{c_f^- \in C_f} \text{sim}(e_{c,n}, c_f^-)}, \quad (17)$$

Experiments

Dataset	Metric	FPMC	GRU4Rec	Caser	SASRec	TiSASRec	SLRS+	Chorus	DIF	CL4Rec	S3Rec	ContraRec	DuoRec	KDA	HPM	Improv.
Beauty	HR@5	0.3392	0.3202	0.3210	0.3666	0.3872	0.4339	0.4536	0.4102	0.3754	0.3812	0.4012	0.4123	0.4921	**0.5141***	4.78%
	HR@10	0.4290	0.4311	0.4345	0.4590	0.4559	0.5337	0.5698	0.5209	0.4660	0.4810	0.4962	0.5039	0.6076	**0.6298***	3.65%
	HR@20	0.5393	0.5693	0.5757	0.5743	0.5700	0.6361	0.6838	0.6421	0.5830	0.6057	0.6065	0.6131	0.7221	**0.7424***	2.81%
	HR@50	0.7511	0.7973	0.8097	0.7756	0.7745	0.8033	0.8536	0.8284	0.8013	0.8146	0.8530	0.8033	0.8853	**0.8961***	1.22%
	NDCG@5	0.2558	0.2271	0.2246	0.2797	0.2904	0.3319	0.3386	0.3016	0.2842	0.3073	0.3406	0.3158	0.3666	**0.3864***	5.40%
	NDCG@10	0.2848	0.2628	0.2612	0.3094	0.3036	0.3642	0.3762	0.3374	0.3134	0.3379	0.3784	0.3454	0.4040	**0.4239***	4.93%
	NDCG@20	0.3125	0.2976	0.2967	0.3385	0.3324	0.3900	0.4050	0.3679	0.3429	0.3657	0.4058	0.3729	0.4329	**0.4524***	4.50%
	NDCG@50	0.3542	0.3426	0.3430	0.3782	0.3728	0.4232	0.4386	0.4048	0.3859	0.4041	0.4397	0.4104	0.4653	**0.4830***	3.80%
Clothing	HR@5	0.2020	0.2142	0.2269	0.2301	0.2722	0.3029	0.3826	0.2977	0.2600	0.2787	0.3798	0.2781	0.3863	**0.4526***	17.16%
	HR@10	0.2834	0.3142	0.3354	0.3571	0.3808	0.3904	0.4916	0.4068	0.3693	0.3797	0.4891	0.3799	0.4991	**0.5748***	15.17%
	HR@20	0.4014	0.4517	0.4892	0.5097	0.5142	0.5004	0.6141	0.5403	0.5161	0.5166	0.6094	0.5155	0.6270	**0.7064***	12.66%
	HR@50	0.6553	0.7143	0.7531	0.7453	0.7405	0.6948	0.8046	0.7600	0.7839	0.7665	0.8028	0.7650	0.8317	**0.8803***	5.84%
	NDCG@5	0.1442	0.1461	0.1548	0.1642	0.1927	0.2329	0.2840	0.2130	0.1854	0.2016	0.2840	0.2012	0.2880	**0.3387***	17.61%
	NDCG@10	0.1703	0.1783	0.1897	0.1946	0.2278	0.2611	0.3192	0.2481	0.2206	0.2341	0.3193	0.2339	0.3244	**0.3781***	16.55%
	NDCG@20	0.2000	0.2130	0.2284	0.2349	0.2613	0.2888	0.3501	0.2817	0.2576	0.2686	0.3496	0.2680	0.3567	**0.4114***	15.34%
	NDCG@50	0.2499	0.2647	0.2807	0.2923	0.3060	0.3271	0.3878	0.3252	0.3103	0.3179	0.3879	0.3172	0.3973	**0.4460***	12.26%
Sports	HR@5	0.3260	0.3015	0.3145	0.3414	0.3475	0.3900	0.4544	0.3945	0.3719	0.3960	0.4544	0.3948	0.4672	**0.4984***	6.68%
	HR@10	0.4373	0.4301	0.4423	0.4566	0.4608	0.4827	0.5823	0.5197	0.5035	0.5160	0.5823	0.5151	0.6021	**0.6306***	4.73%
	HR@20	0.5748	0.5918	0.6039	0.5943	0.6003	0.5961	0.7162	0.6612	0.6555	0.6567	0.7162	0.6553	0.7392	**0.7638***	3.33%
	HR@50	0.8070	0.8412	0.8496	0.8096	0.8131	0.7784	0.8855	0.8575	0.8652	0.8619	0.8855	0.8631	0.9042	**0.9198***	1.72%
	NDCG@5	0.2381	0.2085	0.2175	0.2494	0.2535	0.3013	0.3354	0.2852	0.2681	0.2906	0.3354	0.2894	0.3402	**0.3708***	8.25%
	NDCG@10	0.2740	0.2498	0.2588	0.2866	0.2901	0.3311	0.3767	0.3257	0.3106	0.3294	0.3767	0.3282	0.3838	**0.4136***	8.99%
	NDCG@20	0.3086	0.2905	0.2995	0.3214	0.3253	0.3597	0.4106	0.3615	0.3489	0.3648	0.4106	0.3636	0.4185	**0.4474***	6.91%
	NDCG@50	0.3546	0.3400	0.3484	0.3641	0.3675	0.3957	0.4443	0.4005	0.3907	0.4056	0.4443	0.4049	0.4515	**0.4785***	5.98%

Experiments

Cellphone	HR@5	0.4003	0.3015	0.3937	0.4439	0.4520	0.4696	0.4697	0.4718	0.4085	0.4505	0.4829	0.4745	0.5497	**0.5835***	6.15%
	HR@10	0.5098	0.4301	0.5309	0.5595	0.5767	0.5641	0.5929	0.5951	0.5415	0.5819	0.5994	0.5920	0.6745	**0.7050***	4.52%
	HR@20	0.6321	0.5918	0.6810	0.6817	0.7022	0.6637	0.7152	0.7157	0.6861	0.7147	0.7211	0.7151	0.7923	**0.8225***	3.81%
	HR@50	0.8277	0.8412	0.8849	0.8676	0.8708	0.8172	0.8695	0.8749	0.8825	0.8880	0.8831	0.8792	0.9263	**0.9428***	1.78%
	NDCG@5	0.3027	0.2085	0.2800	0.3353	0.3344	0.3634	0.3530	0.3526	0.2967	0.3287	0.3673	0.3602	0.4119	**0.4487***	8.76%
	NDCG@10	0.3381	0.2498	0.3243	0.3727	0.3748	0.3939	0.3929	0.3925	0.3396	0.3712	0.4050	0.3983	0.4523	**0.4882***	7.94%
	NDCG@20	0.3690	0.2905	0.3622	0.4036	0.4065	0.4191	0.4238	0.4230	0.3761	0.4047	0.4358	0.4294	0.4821	**0.5179***	7.43%
	NDCG@50	0.4077	0.3400	0.4028	0.4370	0.4401	0.4495	0.4545	0.4548	0.4152	0.4393	0.4681	0.4620	0.5089	**0.5419***	6.48%
Toys	HR@5	0.3373	0.2902	0.2898	0.3602	0.3475	0.4368	0.4124	0.3843	0.3627	0.3759	0.4015	0.4001	0.4805	**0.4927***	2.54%
	HR@10	0.4233	0.4060	0.4103	0.4570	0.4608	0.5345	0.5203	0.4924	0.4643	0.4731	0.4958	0.4953	0.5882	**0.6039***	2.67%
	HR@20	0.5283	0.5546	0.5590	0.5700	0.6003	0.6440	0.6443	0.6149	0.5900	0.5972	0.6181	0.6164	0.7019	**0.7211***	2.74%
	HR@50	0.7482	0.8067	0.8107	0.7789	0.8131	0.8012	0.8277	0.8178	0.8208	0.8101	0.8256	0.8244	0.8772	**0.8922***	1.71%
	NDCG@5	0.2583	0.1974	0.1947	0.2738	0.2535	0.3490	0.3132	0.2829	0.2630	0.2811	0.3067	0.3046	0.3660	**0.3807***	4.02%
	NDCG@10	0.2860	0.2348	0.2336	0.3050	0.2901	0.3804	0.3480	0.3178	0.2957	0.3124	0.3371	0.3355	0.4007	**0.4166***	3.97%
	NDCG@20	0.3124	0.2721	0.2710	0.3334	0.3253	0.4081	0.3793	0.3488	0.3273	0.3437	0.3679	0.3660	0.4294	**0.4462***	3.91%
	NDCG@50	0.3556	0.3220	0.3207	0.3747	0.3675	0.4392	0.4156	0.3890	0.3707	0.3858	0.4089	0.4071	0.4642	**0.4803***	3.47%
Grocery	HR@5	0.3618	0.3737	0.3145	0.3925	0.4069	0.4378	0.4513	0.4301	0.3669	0.4029	0.4268	0.4269	0.5168	**0.5432***	5.11%
	HR@10	0.4419	0.4793	0.4423	0.4801	0.5232	0.5523	0.5818	0.5376	0.4624	0.5051	0.5132	0.5127	0.6314	**0.6476***	2.57%
	HR@20	0.5432	0.6013	0.6039	0.5822	0.6350	0.6517	0.6956	0.6465	0.5737	0.6260	0.6170	0.6213	0.7401	**0.7514***	1.53%
	HR@50	0.7511	0.8245	0.8496	0.7709	0.8217	0.7995	0.8576	0.8273	0.7964	0.8202	0.8157	0.8190	0.8901	**0.8999***	1.10%
	NDCG@5	0.2816	0.2684	0.2175	0.2941	0.2906	0.3266	0.3223	0.3122	0.2702	0.2969	0.3291	0.3293	0.3892	**0.4088***	5.04%
	NDCG@10	0.3073	0.3024	0.2588	0.3231	0.3283	0.3637	0.3647	0.3470	0.2992	0.3299	0.3571	0.3570	0.4264	**0.4428***	3.85%
	NDCG@20	0.3328	0.3331	0.2995	0.3488	0.3565	0.3888	0.3934	0.3745	0.3286	0.3604	0.3831	0.3844	0.4539	**0.4689***	3.30%
	NDCG@50	0.3737	0.3772	0.3484	0.3861	0.3934	0.4180	0.4256	0.4104	0.3745	0.3988	0.4224	0.4235	0.4838	**0.4985***	3.04%

Experiments

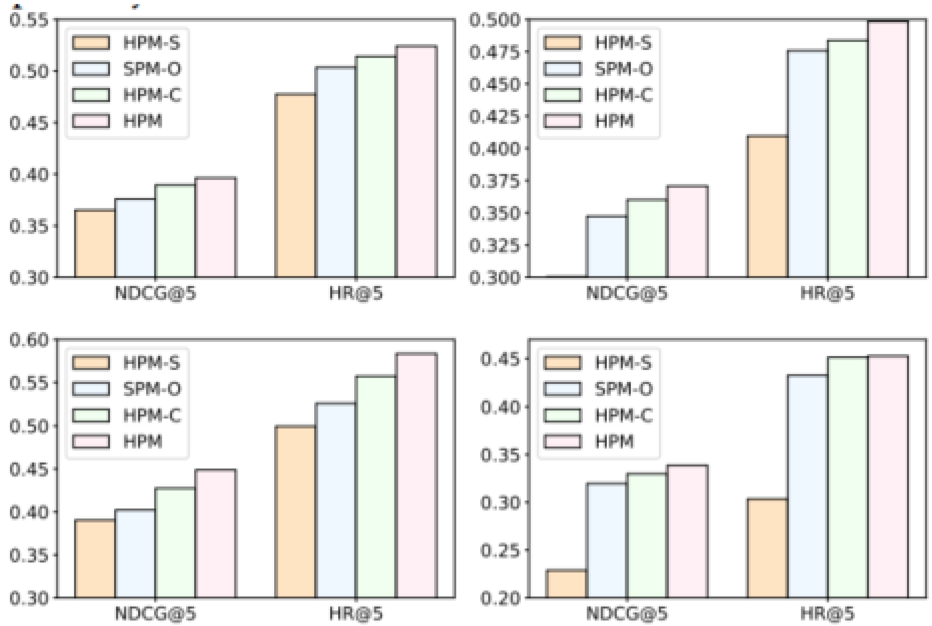
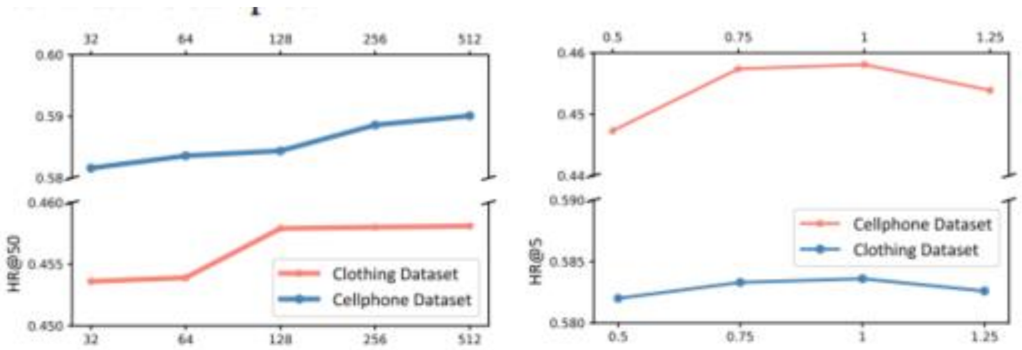


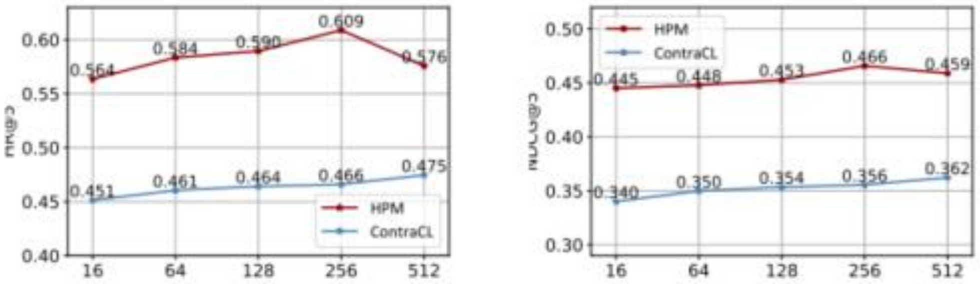
Figure 3: Ablation study of our model (HR@5 and NDCG@5) (Upper left: Beauty, Upper right: Sports, Lower left: Cellphones, Lower right: Clothing).



(a) Parameter sensitivity of model embedding size.

(b) Parameter sensitivity of λ.

Figure 4: Parameter setting's effect on the model performance. (HR@5) on Amazon Clothing dataset.



(a) HR@5 comparison w.r.t. Batch Size on Cellphone.

(b) NDCG@5 comparison w.r.t. Batch Size on Cellphone.

Figure 5: Parameter setting's effect on the model performance. (HR@5 and NDCG@5) on Amazon Cellphone dataset.