基于对比多兴趣的短视频推荐模型

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Improving Micro-video Recommendation via Contrastive Multiple Interests

SIGIR 2022 (CCF A，CORE A*)

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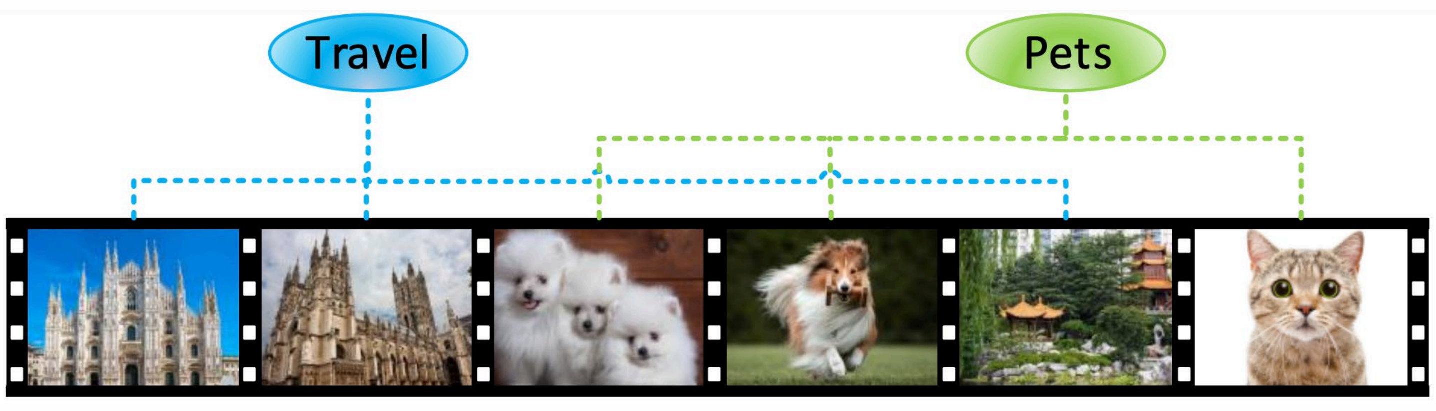
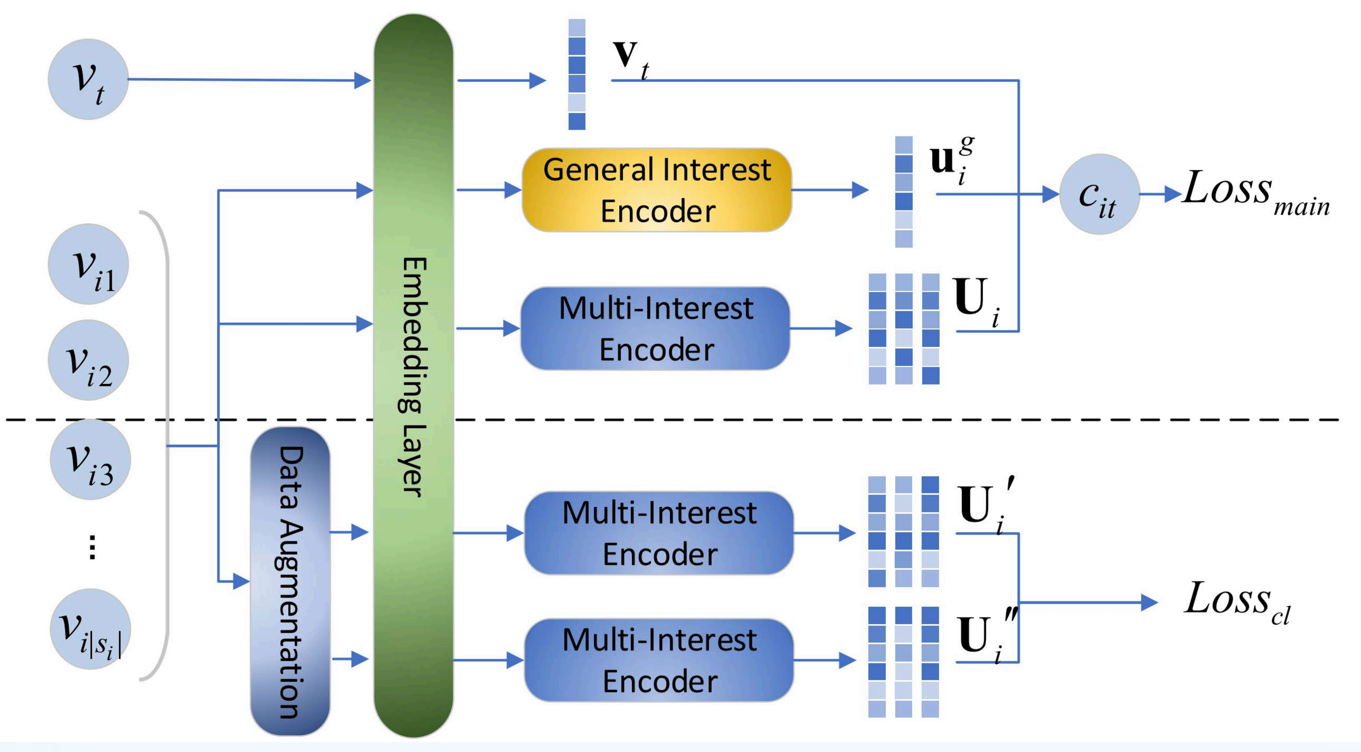
Motivation

- Existing micro-video recommendation models rely on multi-modal information processing, which is too expensive to deal with large-scale micro-videos. Furthermore, they learn a single interest embedding for a user from his/her interaction sequence.
- There is much noise in positive interactions in micro-video scenarios. However, neither existing micro-video recommendation models nor multi-interest recommendation models utilize contrastive learning to reduce the impact of noise in the positive interactions.



Model

- We propose CMI, a micro-video recommendation model, to explore the feasibility of combining contrastive learning with the multi-interest recommendation.
- We establish a multi-interest encoder based on implicit categories of items, and propose a contrastive multi-interest loss to minimize the difference between interests extracting from two augmented views of the same interaction sequence.
- We conduct experiments on two micro-video datasets and the experiment results show the rationality and effectiveness of the model.



Contrastive Regularization

Employ random sampling for data augmentation

$$\mathrm{U}_i' = \text{Multi-Interest-Encoder}\ (s_i')$$
$$\mathrm{U}_i'' = \text{Multi-Interest-Encoder}\ (s_i'')$$

$$\mathcal{L}_{cl}\left(\mathbf{u}_i^{k'}, \mathbf{u}_i^{k''}\right) = -\log \frac{e^{\mathrm{sim}(\mathbf{u}_i^{k'}, \mathbf{u}_i^{k''})}}{e^{\mathrm{sim}(\mathbf{u}_i^{k'}, \mathbf{u}_i^{k''})} + \sum_{\mathbf{s}^- \in \mathcal{S}^-} e^{\mathrm{sim}(\mathbf{u}_i^{k'}, \mathbf{s}^-)}} - \log \frac{e^{\mathrm{sim}(\mathbf{u}_i^{k'}, \mathbf{u}_i^{k''})}}{e^{\mathrm{sim}(\mathbf{u}_i^{k'}, \mathbf{u}_i^{k''})} + \sum_{\mathbf{s}^- \in \mathcal{S}^-} e^{\mathrm{sim}(\mathbf{u}_i^{k''}, \mathbf{s}^-)}}$$

Interest Generation

1. Multiple Interests
   - ✓ Assume there are m global categories and set learnable implicit embeddings $[g_1, g_2, \dots, g_m]$ for these m categories.
   - ✓ Category Assignment
   $$p_{ik}^l = \frac{\exp\left(w_{ik}^l/\epsilon\right)}{\sum_{l=1}^m \exp\left(w_{ik}^l/\epsilon\right)}$$
   - ✓ Interest Generation $\mathbf{u}_i^l = \Sigma_{k=1}^{|s_i|} p_{ik}^l \mathbf{v}_{ik}$
   - ✓ Orthogonality Loss $\mathcal{L}_{orth} = \sum_{i=1}^{m} \sum_{j=1, j\neq i}^{m} (\mathbf{g}_i^T \mathbf{g}_j)^2$
2. General Interest

$$\mathbf{u}_i^g = GRU\left(\left[\mathbf{v}_{i1}, \mathbf{v}_{i2}, \dots, \mathbf{v}_{i|s_i|}\right]\right)$$

Experimental Evaluation

- Performance Comparison

Table 1: Recommendation accuracy on two datasets. #I. denotes the number of interests. The number in a bold type is the best performance in each column. The underlined number is the second best in each column.

	WeChat							TakaTak						
		Recall			HitRate				Recall			HitRate		
	#I.	@10	@20	@50	@10	@20	@50	#I.	@10	@20	@50	@10	@20	@50
Octopus	1	0.0057	0.0125	0.0400	0.0442	0.0917	0.2332	1	0.0076	0.0160	0.0447	0.1457	0.2533	0.4393
MIND	1	0.0296	0.0521	0.1025	0.1774	0.2791	0.4514	1	0.0222	0.0389	<u>0.0773</u>	0.2139	0.3263	0.4977
ComiRec-DR	1	0.0292	0.0525	0.1049	0.1790	0.2893	0.4621	1	0.0226	0.0392	0.0769	0.2345	0.3427	0.5144
ComiRec-SA	1	0.0297	0.0538	0.1079	0.1806	0.2938	0.4684	1	<u>0.0239</u>	<u>0.0409</u>	0.0752	<u>0.2567</u>	0.3665	0.5207
DSSRec	1	<u>0.0327</u>	<u>0.0578</u>	<u>0.1161</u>	<u>0.1971</u>	<u>0.3064</u>	<u>0.4854</u>	8	**0.0244**	0.0408	0.0749	0.2558	<u>0.3704</u>	<u>0.5259</u>
CMI	8	**0.0424**	**0.0717**	**0.1342**	**0.2436**	**0.3612**	**0.5292**	8	0.0210	**0.0415**	**0.0877**	**0.2912**	**0.4172**	**0.5744**
Improv.	/	29.66%	24.05%	15.59%	23.59%	17.89%	9.02%	/	/	1.72%	17.09%	13.84%	12.63%	9.22%

CMI outperforms other multi-interest competitors on most metrics, which demonstrates that CMI generates recommendations with both high accuracy and excellent coverage

- Ablation Study

Both contrastive regularization and the general interest make contributions to performance.

Table 3: Ablation study on WeChat. The values in parentheses are the percentages of decline relative to the original model.

		CMI-CL	CMI-G	CMI
Recall	@10	0.039(-8.02%)	0.0342(-19.34%)	**0.0424**
	@20	0.0665(-7.25%)	0.0589(-17.85%)	**0.0717**
	@50	0.1285(-4.25%)	0.1165(-13.19%)	**0.1342**
HitRate	@10	0.2286(-6.16%)	0.2061(-15.39%)	**0.2436**
	@20	0.3443(-4.68%)	0.3181(-11.93%)	**0.3612**
	@50	0.5188(-1.93%)	0.4935(-6.71%)	**0.5290**

Table 4: The effect of the number of interests on WeChat.

	#I.	1	2	4	8	16
Recall	@10	0.0303	0.0404	0.0409	**0.0428**	0.0412
	@20	0.0530	0.0699	0.0694	**0.0718**	0.0700
	@50	0.1039	0.1343	0.1333	**0.1364**	0.1314
HitRate	@10	0.1969	0.2383	0.2384	**0.2458**	0.2390
	@20	0.3012	0.3547	0.3516	**0.3587**	0.3557
	@50	0.4646	0.5330	0.5271	**0.5322**	0.5238