Modeling Long-term User Behaviors with Diffusion-driven Multi-interest Network for CTR Prediction

基于扩散模型驱动的多兴趣网络建模用户长期行为以预测点击率

赖伟江，金蓓弘

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Contact：Beihong@iscas.ac.cn

Introduction

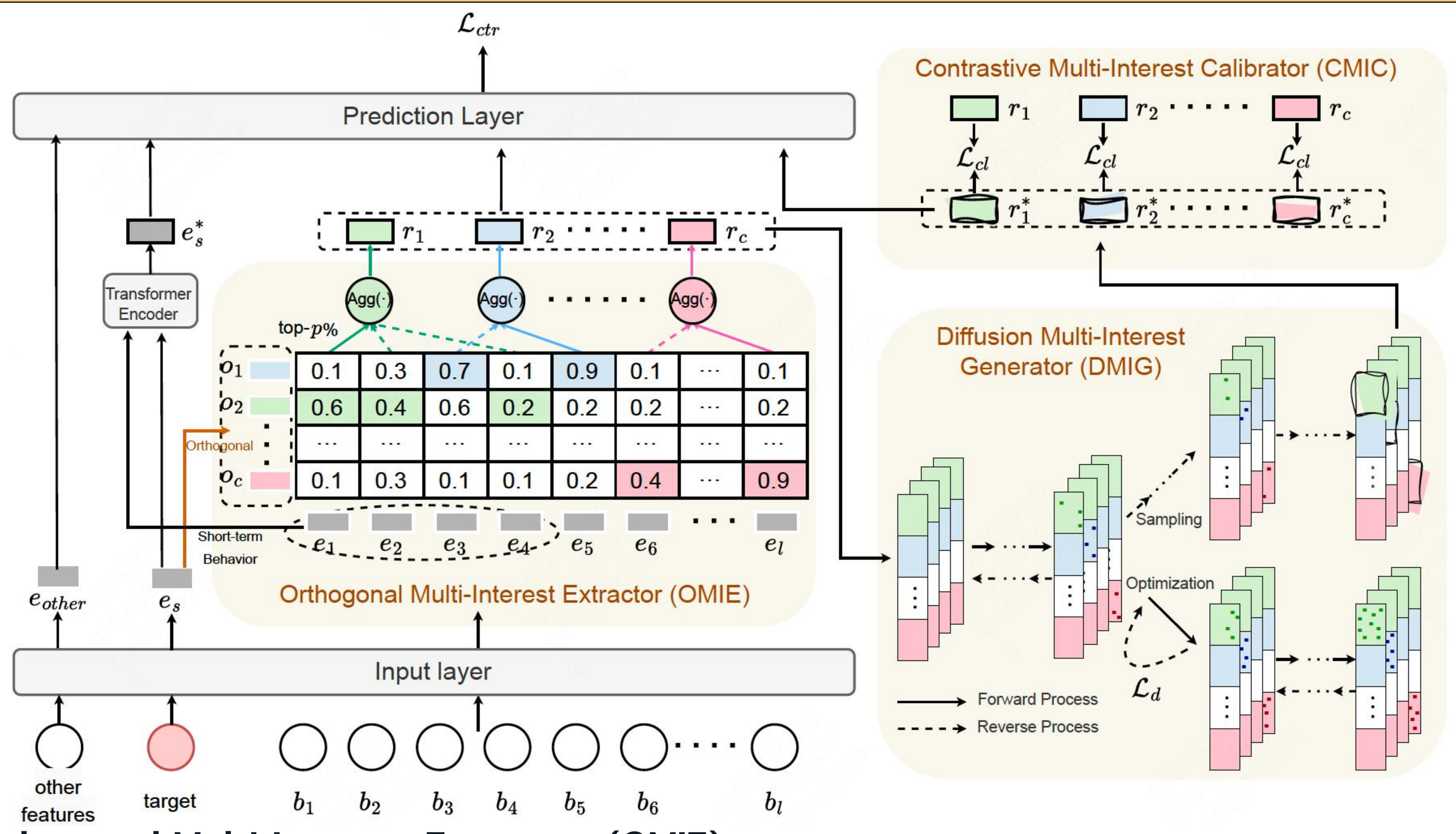
•Click-Through Rate (CTR) prediction is vital for recommender systems and online advertising, with recent research highlighting the importance of modeling long-term user behaviors.

•Modeling long-term behaviors is challenging due to the vast number of behaviors, noise interference, and computational inefficiency.

•Existing two-stage models improve efficiency by filtering behaviors but often fail to capture the diversity of user interests, leading to limited latent interest spaces.

•Inspired by multi-interest and generative modeling, DiffuMIN (Diffusion-driven Multi-Interest Network) is proposed to thoroughly explore and augment the user interest space for better CTR prediction.

Methodology



Algorithm 1 Diffusion Optimization Phase

Input: $r_1, ..., r_c, o_1, ..., o_c$
Output: $\mathcal{L}_d$
$\mathcal{L}_d = 0$
for $i \leftarrow 1$ to c **do**
$r_{i,0} \sim q(r_i)$
$t \sim \text{Uniform}(\{1, ..., T\})$
$\epsilon \sim N(0,1)$
$g_1 = [r_1, ..., r_{i-1}, r_{i+1}, ..., r_c], \quad g_2 = o_i$
$\mathcal{L}_d += \left\|\epsilon - \epsilon_\theta\left(\sqrt{\bar{\alpha}_t} r_{i,0} + \sqrt{1-\bar{\alpha}_t}\epsilon, t, g_1, g_2\right)\right\|_2^2$
end for

Algorithm 2 Diffusion Sampling Phase

Input: $r_1, ..., r_c, o_1, ..., o_c$
Output: $r_1^*, ..., r_c^*$
for $i \leftarrow 1$ to c **do**
$t \sim \text{Uniform}(\{1, ..., T\})$
$r_{i,t} = \sqrt{\bar{\alpha}_t} r_{i,0} + \sqrt{1-\bar{\alpha}_t}\epsilon$
$r_{i,T'}^* \sim q(r_{i,t})$
$g_1 = [r_1, ..., r_{i-1}, r_{i+1}, ..., r_c], \quad g_2 = o_i$
for $t \leftarrow T'$ to 1 **do**
$t > 1 ? z \sim \mathcal{N}(0,1) : z = 0$
$r_{i,t-1}^* = \frac{1}{\sqrt{\alpha_t}}(r_{i,t}^* - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(r_{i,t}^*, t, g_1, g_2)) + \sigma_t z$
end for
$r_i^* = r_{i,0}^*$
end for

•**Orthogonal Multi-Interest Extractor (OMIE):**

- Decomposes the target embedding into multiple orthogonal interest channels.
- Models the relationship between user behaviors and these channels, disentangling and extracting multiple user interests via behavior routing, channel filtering, and interest aggregation.

•**Diffusion Multi-Interest Generator (DMIG):**

- Introduces a diffusion module guided by contextual interests and interest channels.
- Generates augmented interests that align with the latent user interest spaces, starting from perturbed user interests rather than random noise for better personalization.

•**Contrastive Multi-Interest Calibrator (CMIC):**

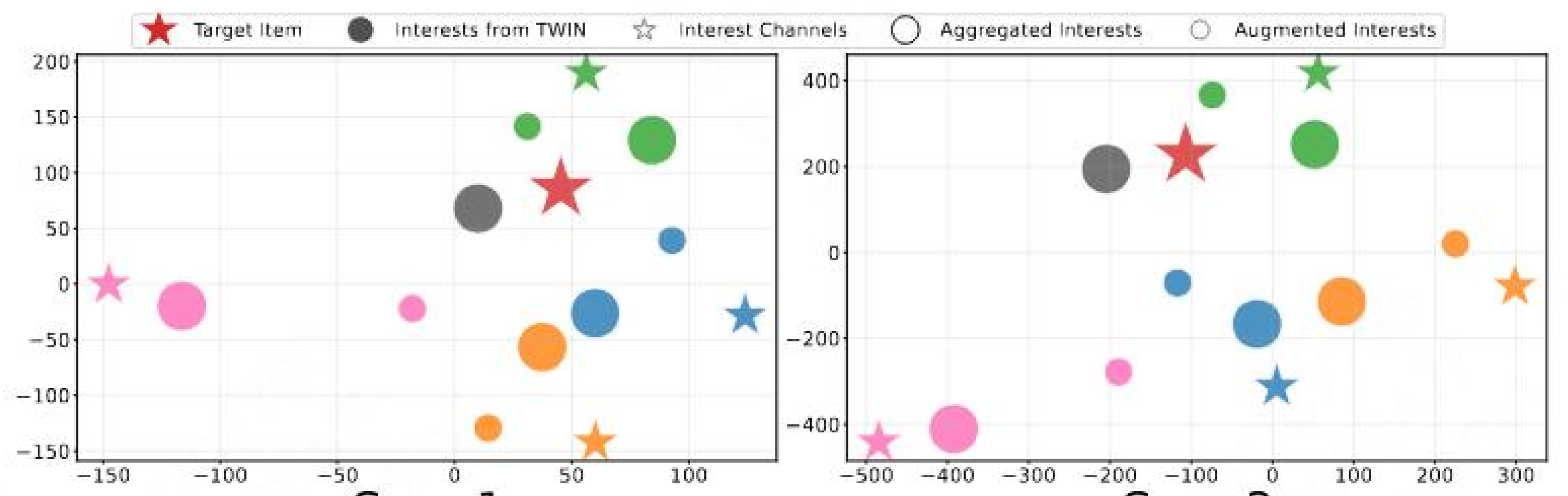
- Employs contrastive learning to align generated augmented interests with genuine user preferences, enhancing the quality and diversity of interest representations.

•**Prediction Layer:** Aggregated interests, augmented interests, short-term interests, and other features are combined and fed into an MLP for final CTR prediction.

Experiments

Dataset	Metric	DIN(S)	CAN(S)	DIN	CAN	SoftSIM	HardSIM	ETA	SDIM	TWIN	TWIN-V2	DiffuMIN
Industry	AUC	0.6740	0.6736	0.6751	0.6748	0.6772	0.6780	0.6778	0.6779	0.6785	0.6788	**0.6841**
	RelaImpr	0.00%	-0.23%	0.63%	0.45%	1.84%	2.30%	2.18%	2.24%	2.59%	2.76%	**5.80%**
Alibaba	AUC	0.6125	0.6091	0.6198	0.6184	0.6212	0.6239	0.6220	0.6206	0.6215	0.6220	**0.6282**
	RelaImpr	0.00%	-3.02%	6.49%	5.24%	7.73%	10.13%	8.44%	7.20%	8.00%	8.44%	**13.96%**
Ele.me	AUC	0.6363	0.6378	0.6273	0.6284	0.6399	0.6389	0.6398	0.6404	0.6410	0.6400	**0.6462**
	RelaImpr	0.00%	1.10 %	-6.60%	-5.80%	2.64%	1.90%	2.57%	3.01%	3.45%	2.71%	**7.26%**

- We conduct extensive offline experiments on three real-world datasets and online A/B testing. Experimental results show that DiffuMIN achieves SOTA performance.



Case 1 Case 2

- Case studies visualize that DiffuMIN preserves and expands the user interest space more effectively than traditional models.