Improving Item Cold-start Recommendation via Model-agnostic Conditional Variational Autoencoder

Xu Zhao
Tencent News
Beijing, China
xuzzzhao@tencent.com

Yi Ren
Tencent News
Beijing, China
henrybjren@tencent.com

Ying Du
Tencent News
Beijing, China
yingdu@tencent.com

Shenzheng Zhang
Tencent News
Beijing, China
qjzcyzhang@tencent.com

Nian Wang
Tencent News
Beijing, China
noreenwang@tencent.com

2022 SIGIR

2022. 8. 15 • ChongQing

Leibniz-Institut
für Sozialwissenschaften

Reported by Gu Tang

Motivation


太空救援
810 · 灾难 / 宇宙
上映时间2022
位于外太空的"礼炮7号"空间站意外与地球失去联系，工程师维克托·阿约金和退役宇航员弗拉基米尔·费奥多罗夫临危受命，搭乘联盟号T-13寻找"礼炮7号"的踪迹，当经历宇宙空间对接、太空舱寒流、空间站失火、太阳能充电系统失灵等一系列危机准备返航之时，却被告知空间站即将被击落，一场更大的太空灾难正在袭来...
演职员
克利姆·...
导演
弗拉季米...
饰Vladi...
柳波芙·...
饰Liliya ...
巴维尔·...
饰Viktor ...
玛丽亚·...
饰Nina

Model

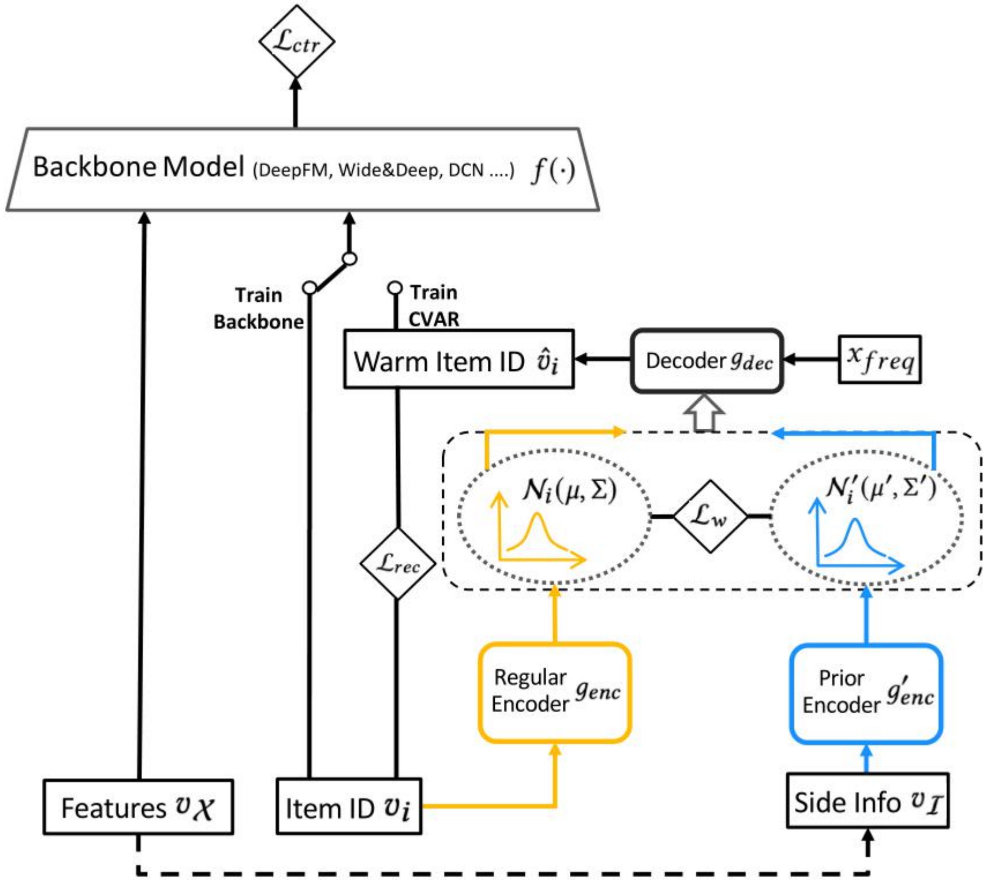

Figure 1: The proposed model-agnostic CVAR Framework, where Backbone Model can be any CTR prediction model with embedding layer.

Method

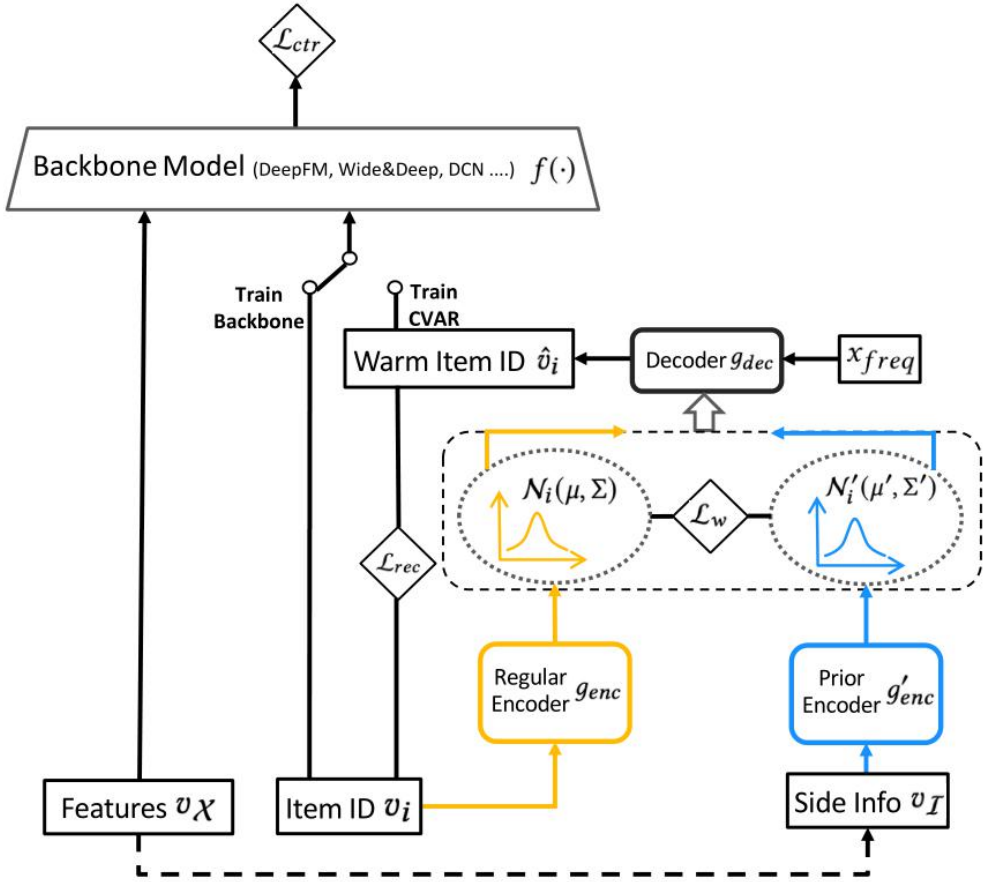

Figure 1: The proposed model-agnostic CVAR Framework, where Backbone Model can be any CTR prediction model with embedding layer.

推土机距离Wasserstein Distance

$$\hat{y} = f(v_i, v_{\mathcal{X}}; \theta) \quad (1)$$

$$\mathcal{L}(\theta, \phi) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y}) \quad (2)$$

$$\mu, \sigma = g_{enc}(v_i; w_{enc}); \mu \in \mathbb{R}^k, \sigma \in \mathbb{R}^k \quad (3)$$

$$z \sim \mathcal{N}_i(\mu, \Sigma); \Sigma \in \mathbb{R}^{k\times k}, diag(\Sigma) = \sigma \quad (4)$$

$$\hat{v}_i = g_{dec}(z, x_{freq}; w_{dec}); \hat{v}_i \in \mathbb{R}^d \quad (5)$$

$$\mathcal{L}_{rec}(w_{enc}, w_{dec}) = \|v_i - \hat{v}_i\|_2^2 \quad (6)$$

$$\mu', \sigma' = g'_{enc}(v_{\mathcal{I}}; w'_{enc}); \mu' \in \mathbb{R}^k, \sigma' \in \mathbb{R}^k \quad (7)$$

$$z' \sim \mathcal{N}'_i(\mu', \Sigma'); \Sigma' \in \mathbb{R}^{k\times k}, trace(\Sigma') = \sigma' \quad (8)$$

$$\hat{v}'_i = g_{dec}(z', x_{freq}; w_{dec}); \hat{v}'_i \in \mathbb{R}^d \quad (9)$$

$$\mathcal{L}_w(w_{enc}, w'_{enc}) = W_2(\mathcal{N}_i(\mu, \Sigma), \mathcal{N}'_i(\mu', \Sigma')) \quad (10)$$

$$\hat{y}_{warm} = f(\hat{v}'_i, v_{\mathcal{X}}; \theta) \quad (11)$$

$$\mathcal{L}_{warm}(w_{enc}, w_{dec}, w'_{enc}) = \mathcal{L}_{ctr} + \alpha\mathcal{L}_{rec} + \beta\mathcal{L}_w \quad (13)$$

$$v_i \in \mathbb{R}^d, v_{\mathcal{I}} \in \mathbb{R}^{d\times|\mathcal{I}|} \text{ and } v_{\mathcal{X}} \in \mathbb{R}^{d\times|\mathcal{X}|}$$

Methods

Wasserstein Distance

$$P_1 = 3, P_2 = 2, P_3 = 1, P_4 = 4$$

$$Q_1 = 1, Q_2 = 2, Q_3 = 4, Q_4 = 3$$

$$\delta_{i+1} = \delta_i + P_i - Q_i$$

$$W = \sum |\delta_i| = 5$$

$$\delta_0 = 0$$

$$\delta_1 = 0 + 3 - 1 = 2$$

$$\delta_2 = 2 + 2 - 2 = 2$$

$$\delta_3 = 2 + 1 - 4 = -1$$

$$\delta_4 = -1 + 4 - 3 = 0$$

Experiment

Table 1: Model Comparison of cold-start effectiveness on two datasets(*Movielens 1M* and *Taobao Ad*), under two backbones(*DeepFM* and *Wide&Deep*), three runs for each. The best improvements are highlighted in bold.

Methods	Cold phase AUC	Cold phase F1	Warm-a phase AUC	Warm-a phase F1	Warm-b phase AUC	Warm-b phase F1	Warm-c phase AUC	Warm-c phase F1
Dataset: Movielens 1M & Backbone: DeepFM								
DeepFM	0.7267	0.6231	0.7424	0.6383	0.7574	0.6503	0.7694	0.6608
DropoutNet	0.7387	0.6339	0.7491	0.6441	0.7587	0.6531	0.7673	0.6599
Meta-E	0.7327	0.6344	0.7441	0.6432	0.7544	0.6519	0.7633	0.6592
MWUF	0.7316	0.6289	0.7462	0.6413	0.7589	0.6521	0.7701	0.6616
CVAR (Init Only)	0.7401	0.6353	0.7518	0.6454	0.7624	0.6547	0.7717	0.6622
CVAR	**0.7419**	**0.6356**	**0.7927**	**0.6789**	**0.8021**	**0.6856**	**0.8041**	**0.6878**
Dataset: Movielens 1M & Backbone: Wide&Deep								
Wide&Deep	0.7071	0.5972	0.7232	0.6164	0.7354	0.6273	0.7461	0.6372
DropoutNet	**0.7125**	**0.6038**	0.7228	0.6159	0.7313	0.6244	0.7390	0.6314
Meta-E	0.6727	0.5287	0.7201	0.6120	0.7345	0.6280	0.7450	0.6374
MWUF	0.7063	0.5966	0.7230	0.6157	0.7355	0.6275	0.7459	0.6366
CVAR (Init Only)	0.7020	0.5795	0.7255	0.6160	0.7375	0.6293	0.7473	0.6380
CVAR	0.6937	0.5643	**0.7627**	**0.6525**	**0.7756**	**0.6639**	**0.7840**	**0.6712**
Dataset: Taobao Ad & Backbone: DeepFM								
DeepFM	0.5983	0.1350	0.6097	0.1378	0.6207	0.1401	0.6311	0.1438
DropoutNet	**0.5989**	**0.1352**	0.6098	0.1374	0.6203	0.1396	0.6302	0.1435
Meta-E	0.5982	0.1346	0.6093	0.1377	0.6195	0.1400	0.6294	0.1428
MWUF	0.5986	0.1348	0.6082	0.1374	0.6184	0.1399	0.6279	0.1429
CVAR (Init Only)	0.5987	0.1350	0.6098	0.1376	0.6204	0.1398	0.6306	0.1432
CVAR	0.5978	0.1347	**0.6198**	**0.1408**	**0.6308**	**0.1477**	**0.6380**	**0.1503**
Dataset: Taobao Ad & Backbone: Wide&Deep								
Wide&Deep	0.6081	0.1360	0.6129	0.1427	0.6207	0.1455	0.6287	0.1484
DropoutNet	**0.6095**	0.1359	0.6184	0.1427	0.6246	0.1454	0.6312	0.1474
Meta-E	0.6082	0.1378	0.6122	0.1443	0.6190	0.1477	0.6259	0.1506
MWUF	0.6089	**0.1382**	0.6125	0.1423	0.6210	0.1457	0.6285	0.1483
CVAR (Init Only)	0.6027	0.1359	0.6065	0.1429	0.6163	0.1471	0.6232	0.1496
CVAR	0.6051	0.1368	**0.6220**	**0.1457**	**0.6290**	**0.1495**	**0.6336**	**0.1511**

Table 2: CVAR performance(AUC) with different x_{freq} on Movielens1M and Wide&Deep, three runs for each. The best improvements are highlighted in bold.

x_{freq}	Cold	Warm-a	Warm-b	Warm-c
0.01	0.6936	0.7627	0.7756	0.7839
0.1	0.6939	0.7629	0.7756	0.7837
0.25	0.6946	0.7627	0.7754	0.7842
0.5	0.6956	0.7638	0.7754	0.7844
1.0	**0.6973**	**0.7649**	**0.7757**	**0.7845**

Experiment

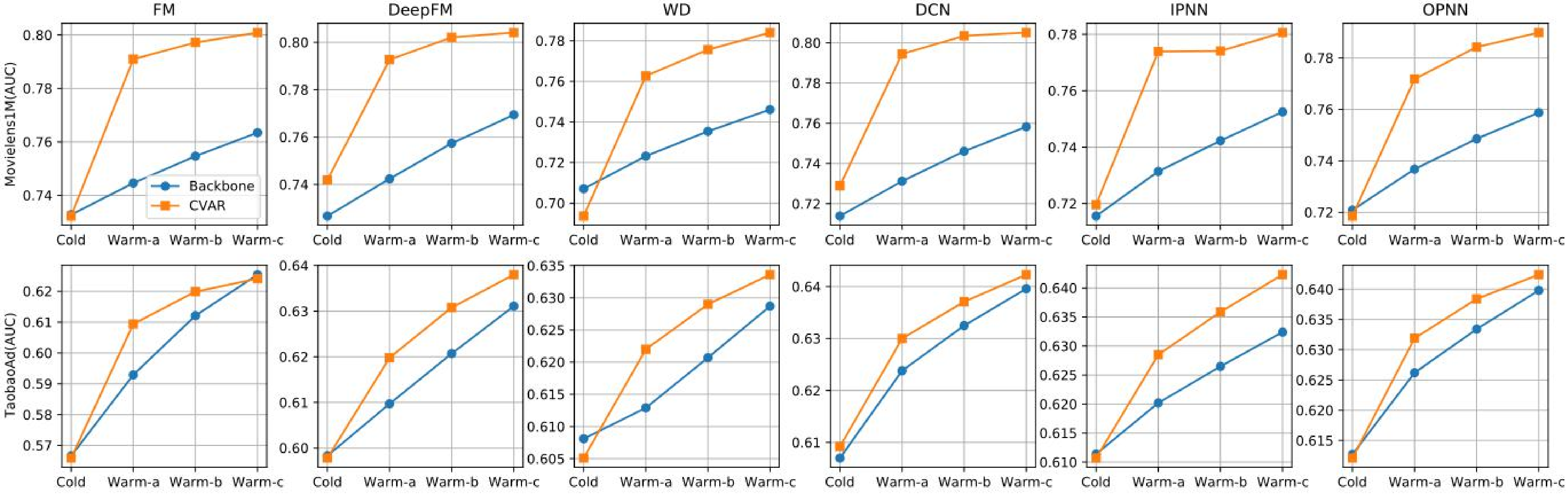

Figure 2: AUC curves through warming-up on two datasets, over six popular backbone models, three runs for each.

Experiment

Table 3: Online A/B results of item groups with increasing warm-up level: *cold*, *warm-a*, *warm-b* and *warm-c*. Red results mean they are statistically significant (whose p-value in hypothesis testing [1] is stable less than 0.05.)

Metrics	Cold	Warm-a	Warm-b	Warm-c	Total
Exposure Rate	+1.48%	-0.21%	-0.04%	+0.17%	-
Watch Time	+2.49%	+2.90%	+1.40%	+0.39%	+0.38%
Article Watch Time	+2.39%	+4.51%	+2.08%	+0.16%	+0.13%
Video Watch Time	+2.60%	+1.78%	+0.72%	+0.68%	+0.66%
Total Page Views	+4.46%	+2.87%	+1.42%	+0.62%	+1.09%
Article Page Views	+3.58%	+3.37%	+1.74%	+0.31%	+0.82%
Video Views	+5.84%	+2.25%	+1.05%	+1.01%	+1.35%

Thank