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Adversarial Preference Learning with Pairwise Comparisons

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P2B-08

Outline

- Motivation
- Framework
- Advantage
- Experiment
- Conclusion

Recommender System

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Complex options confuse him!

Recommend N items
that the user might like!

Collaborative Ranking

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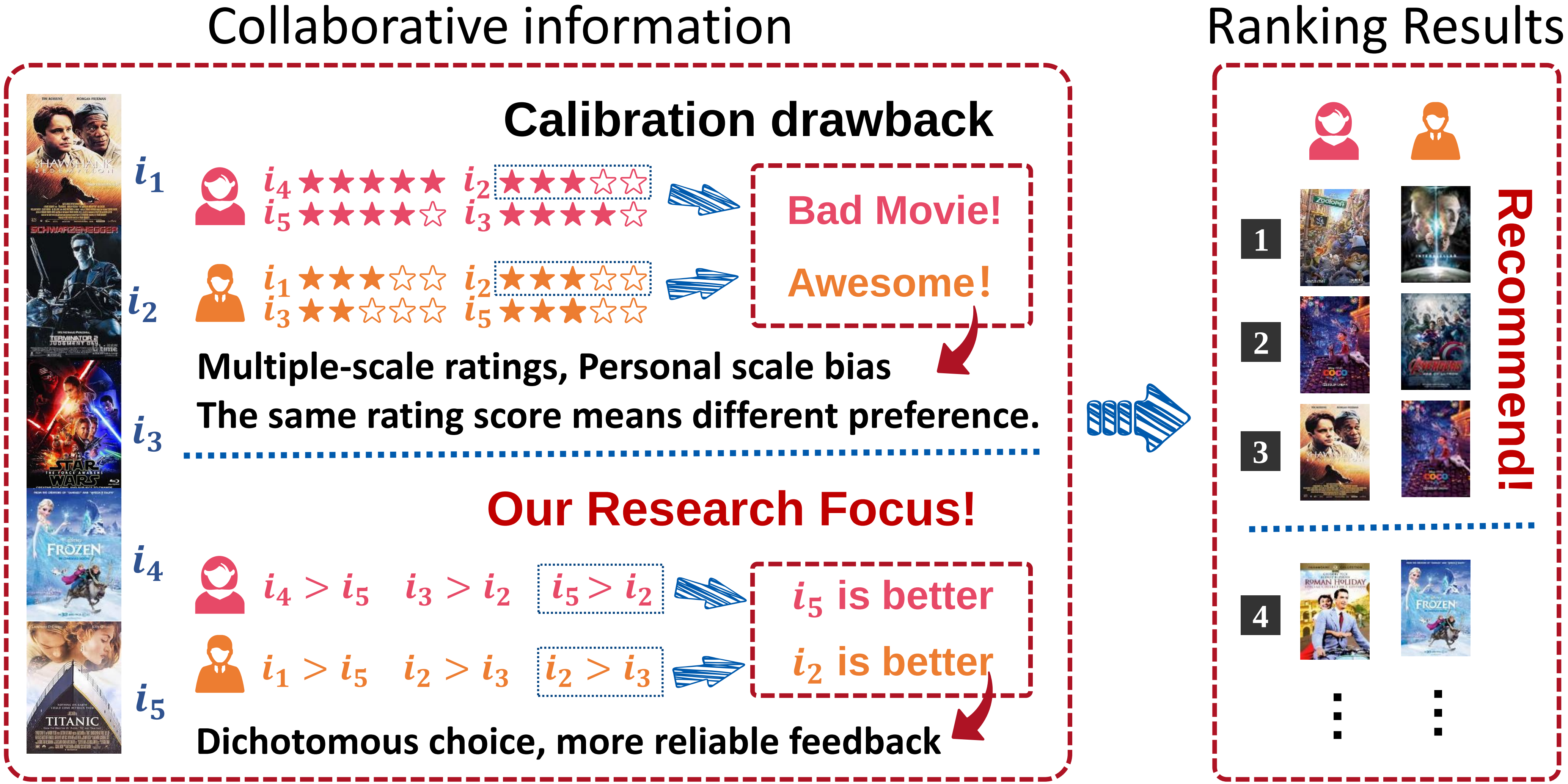
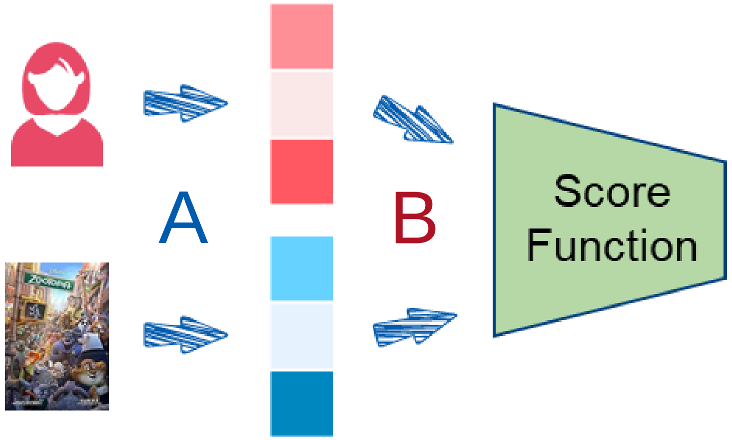


Traditional CR Method

- How to get ranking scores?



$$s_{ui} = s(\boldsymbol{v}_u, \boldsymbol{v}_i)$$

Task A: Learning proper user-item representations

Task B: Learning a proper score function

- Traditional generative methods:

Static loss function.

$$\min_{\Theta_g} \sum_{(u,i,j)\in\mathcal{T}} \mathcal{L}_g\left(\mathcal{P}\left(\sigma(s_{ui} - s_{uj}), y_{uij} | \Theta_g\right)\right)$$

static scoring function

- Both the two factors restrict their further improvement of precision

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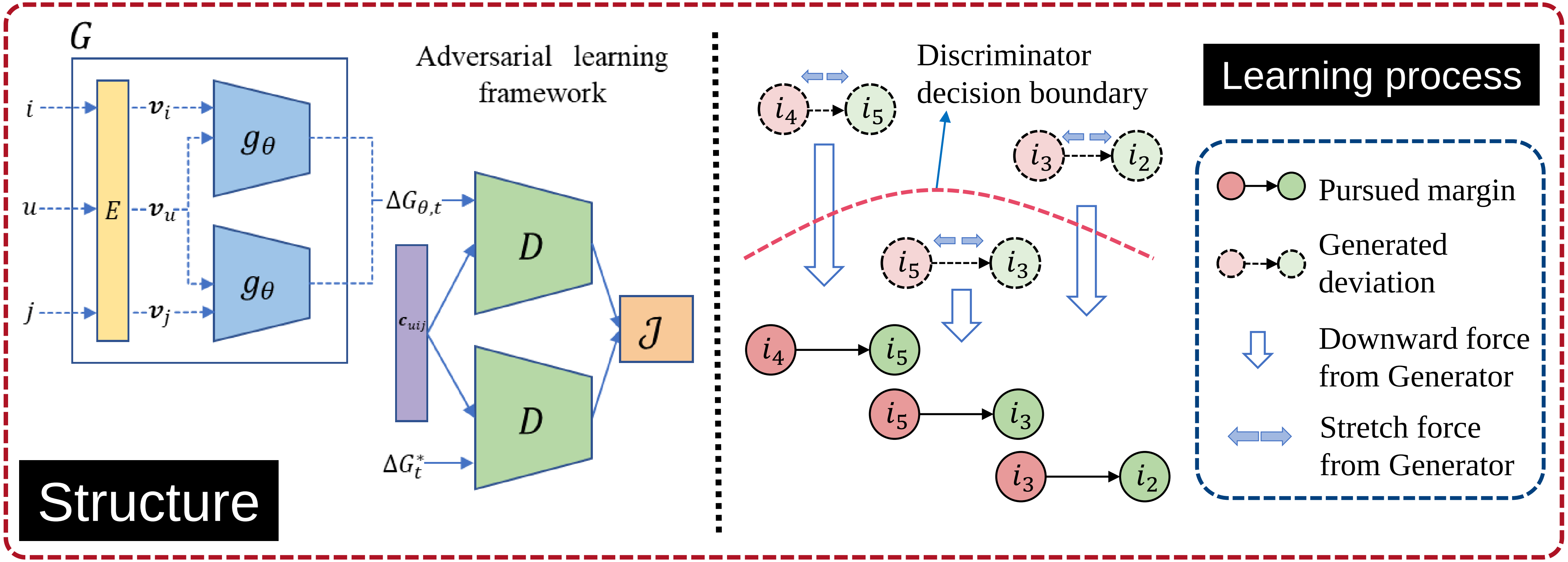
Framework

A **deep** model learns **dynamically** against increasing difficulty and adversarial attacks from the discriminator



Generator

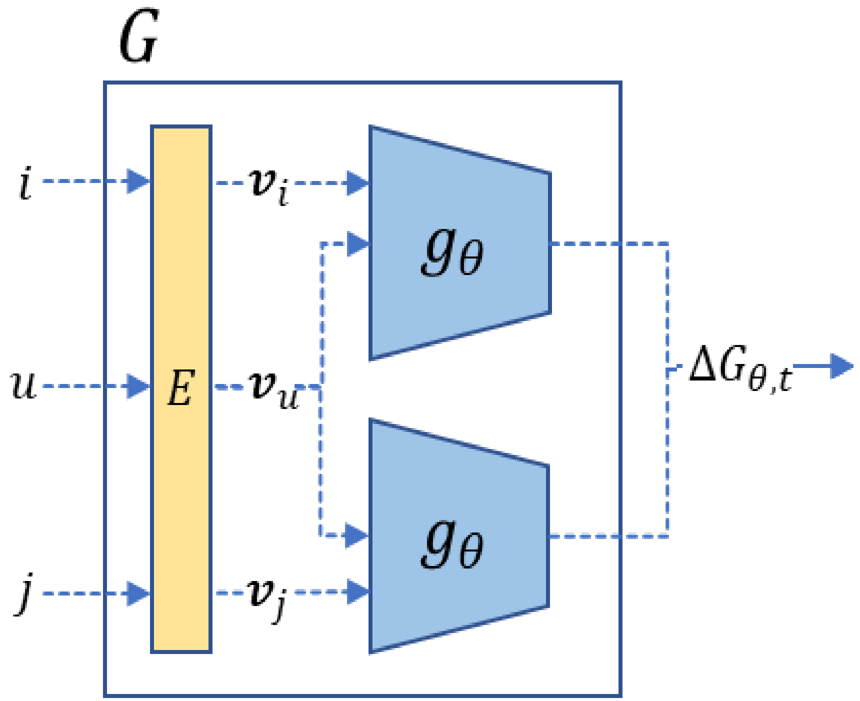
- **Non-linear score function (NN)**

$$g_\theta(u,i) = \sigma\left(\underbrace{g_m}_{\text{multi-FC}}\left(\underbrace{g_E^{\text{user}}(u)}_{\text{embedding}}, \underbrace{g_E^{\text{item}}(i)}_{\text{layer}}\right)\right)$$

multi-FC, embedding layer

- **Score difference**

$$\Delta G_{\theta,t} = g_\theta(u,i) - g_\theta(u,j), \quad \forall t = (u,i,j) \in \mathcal{T}$$



how to design D to attck G?

Discriminator

- **Answer: attack supervision signals**

  A discriminator better forcing the score difference of each pair to be different from the ideal margin.

- **Construct two types of instances:**

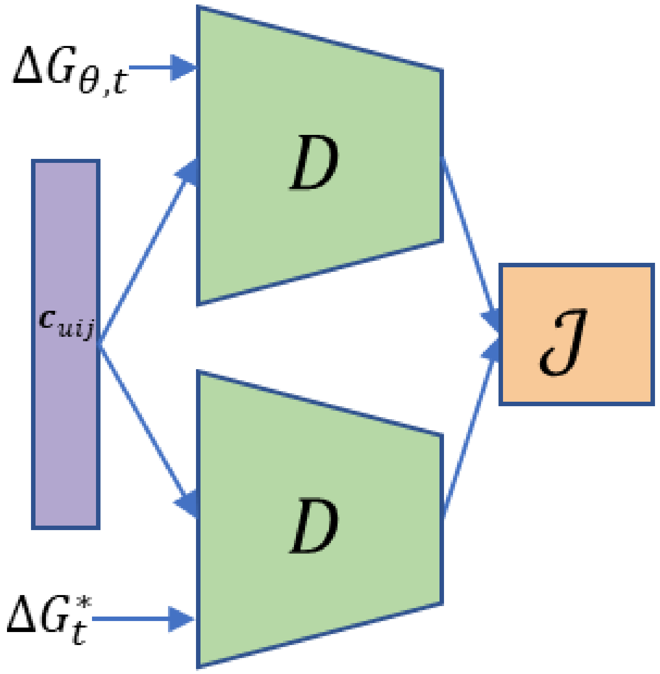
score difference

$$d_\phi\left(\Delta G_t, \mathbf{c}_{uij}, z_{uij}\right) = \sigma\left(z_{uij} \cdot f_m\left(\Delta G_t, \mathbf{c}_{uij}\right)\right)$$

code of triplet (u, i, j) label of ΔG_t

$$\Delta G_t = \begin{cases} \Delta G_{\theta,t} & \text{if } z_{uij} = -1, \\ \Delta G_t^* & \text{if } z_{uij} = \ \ 1, \end{cases}$$

ideal margin in classification.



Objective Function

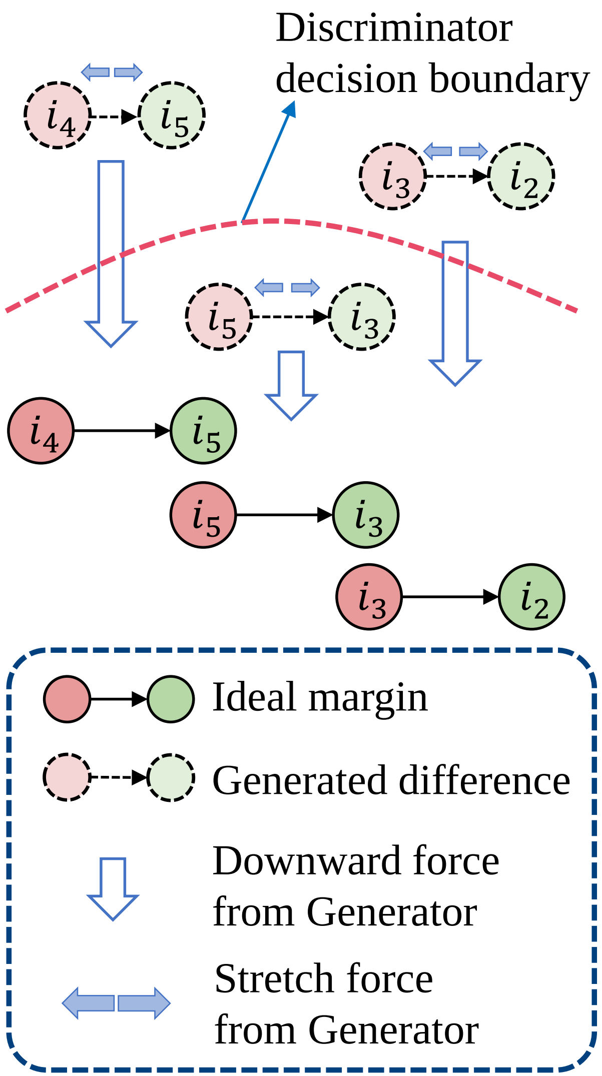
➢ **A minimax game**

$$\min_{\theta}\max_{\phi} J(G,d) = \mathbb{E}_{t\sim\mathcal{P}_{\mathcal{T}}}\left[\log(1 - d_{\phi}(\Delta G_{\theta,t}, \Delta G_t^*))\right]$$

➢ G minimizes the gap between the generated score difference and the ideal margin.

➢ D tries to distinguish them.

➢ When the game reaches equilibrium, the generated score difference gets close to a robust solution against loss perturbation.



Objective Function

- **A minimax game**

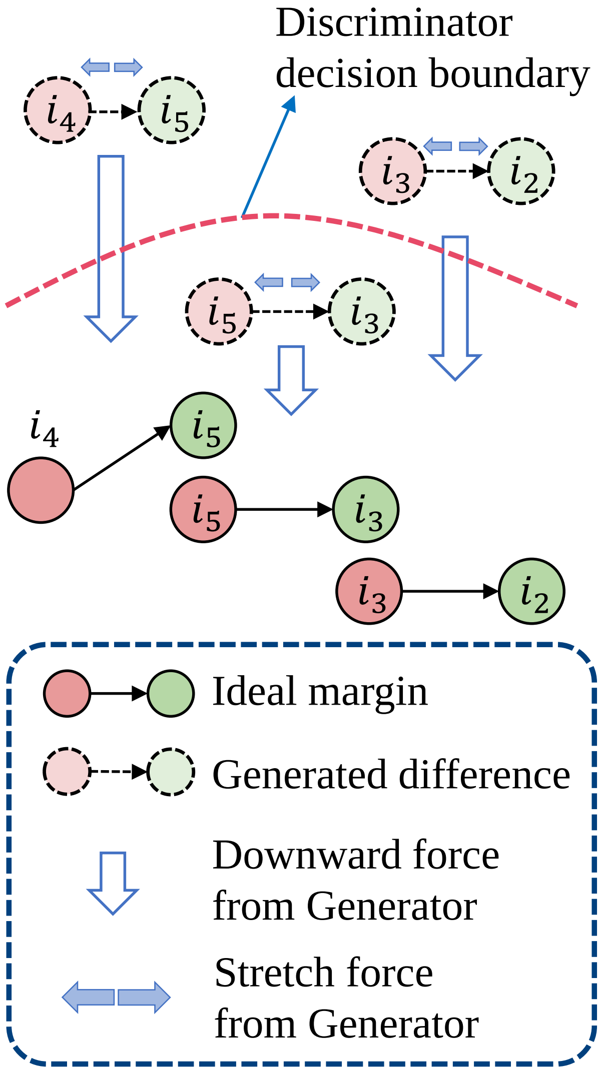
$$\min_{\theta}\max_{\phi} J(G,d) = \mathbb{E}_{t\sim\mathcal{P}_{\mathcal{T}}}\left[\log(1 - d_{\phi}(\Delta G_{\theta,t}, \Delta G_t^*))\right]$$

- **Fix $\boldsymbol{G}$, update $\boldsymbol{d}$**

$$\phi^* = \arg\max_{\phi} \mathbb{E}_{t\sim\mathcal{P}_{\mathcal{T}}}\left[\log(1 - d_{\phi}(\Delta G_{\tilde{\theta},t}, \Delta G_t^*))\right]$$

- **Fix $\boldsymbol{d}$, update $\boldsymbol{G}$**

$$\tilde{\theta} = \arg\min_{\theta} \mathbb{E}_{t\sim\mathcal{P}_{\mathcal{T}}}\left[\log(1 - d_{\phi^*}(\Delta G_{\theta,t}, \Delta G_t^*))\right]$$



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Advantage

In view of probability, if we fix d and update G, the objective can be simplified by Bayes' rule:

$$\min_{\theta} \sum_{(u,i,j)\in\mathcal{T}} \log\left(\mathcal{P}\left(\Delta G_{\theta,t}, y_{uij} | z_{uij} = -1; \phi^*\right)\right)$$

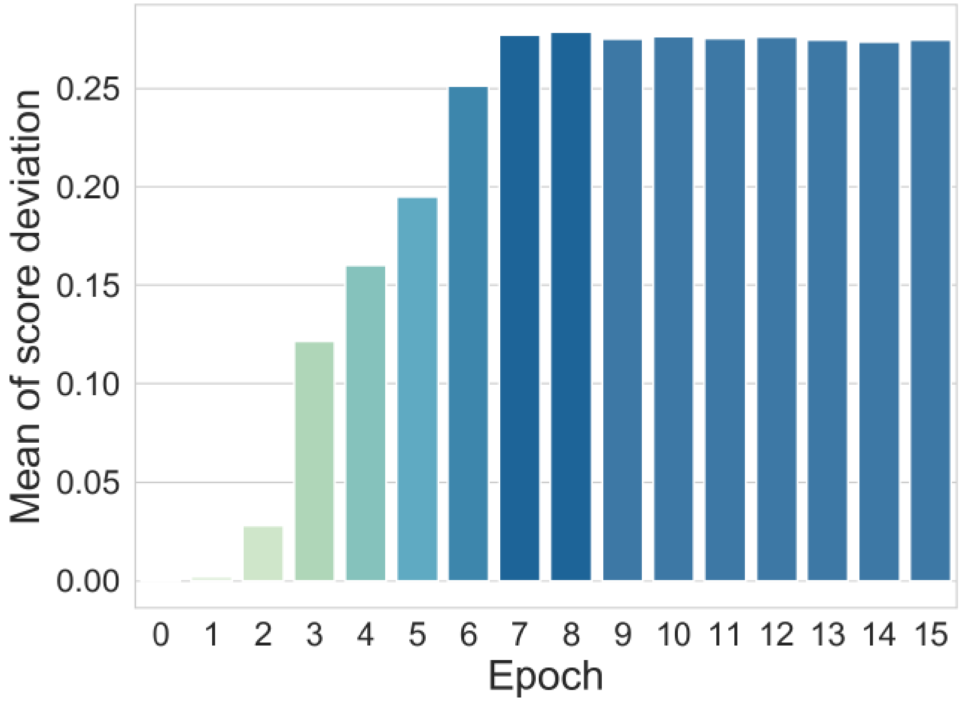
After d is updated:

$$\boxed{\min_{\theta} \sum_{(u,i,j)\in\mathcal{T}} \mathcal{L}'_{\mathrm{g}}\left(\mathcal{P}\left(\sigma'\left(\Delta G_{\theta,t}\right), y_{uij}\right)\right)}$$

Intuitively, our framework is generic. If we adopt a predefined score function and fix the d, it will degenerate to a traditional generative model, which explains the superior performance of our framework.

Advantage

- Deep generator
  → learns adaptive score for specific preference
- Stricter supervision signals from discriminator
  → score differences continually approximate the ideal margin:



Visualization of the change of the mean values of score difference $w.r.t$ epochs. The generator is randomly initialized so that the mean of score difference almost equals to 0 in the first few epochs. Then, the score difference gradually increases as the game goes on, until an equilibrium point is reached.

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Competitors

- **IRGAN**
  Representative adversarial model for information retrieval
- **MLP, GMF, NeuMF**
  Famous deep framework for collaborative filtering
- **CofiRank, RegularizedSVD, RankBasedSVD, LCR Primal-CR, Primal-CR++, AltSVM, Global Ranking**
  Common baselines for collaborative ranking

Dataset

We perform evaluations on three popular benchmark datasets: MoiveLens100K, MovieLens1M and Netflix. The details are summarized in the table. Pairwise preferences are generated by comparing the ratings for each pair of items.

	MoiveLens100K	MoiveLens1M	Netflix
#User	943	6,040	10,000
#Item	1,683	3,706	17,770
#Rating	100,000	1,000,209	8,930,336
Sparsity	93.70%	95.53%	94.97%
#Pair	426,010	3,334,252	7,916,812
#Pair / #user	451	552	792
#Train item / #item	29.59%	21.31%	5.40%
#Negative sample	54,383	687,774	563,067

Results

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Here are the results. We can see that our method significantly outperforms all the other models on all the metrics.

	HR@10↑	P@10↑	NDCG@10↑	AUC@10↑	MAP@10↑	MRR@10↑
IRGAN	0.8511	0.2642	0.2670	0.5989	0.2858	0.1020
MLP	0.9598	0.3519	0.3909	0.7271	0.3938	0.1491
GMF	0.9175	0.3437	0.3580	0.7287	0.3762	0.1331
NeuMF	0.9416	0.3590	0.3757	0.7340	0.3858	0.1382
CoFiRank	0.9256	0.3354	0.3598	0.7152	0.3717	0.1357
RegularizedSVD	0.8934	0.3404	0.3505	0.7287	0.3702	0.1298
RankBasedSVD	0.9256	0.3318	0.3510	0.7042	0.3639	0.1318
LCR	0.9437	0.3503	0.3744	0.7245	0.3830	0.1404
Primal-CR	0.9577	0.3899	0.4205	0.7160	0.4128	0.1539
Primal-CR++	0.9575	0.3896	0.4199	0.7165	0.4139	0.1526
AltSVM	0.9618	0.3899	0.4209	0.7186	0.4136	0.1542
Global Ranking	0.9678	0.3795	0.4045	0.7353	0.4083	0.1483
CRGAN(ours)	0.9839	0.4678	0.4864	0.7559	0.4753	0.1688

MovieLens100K

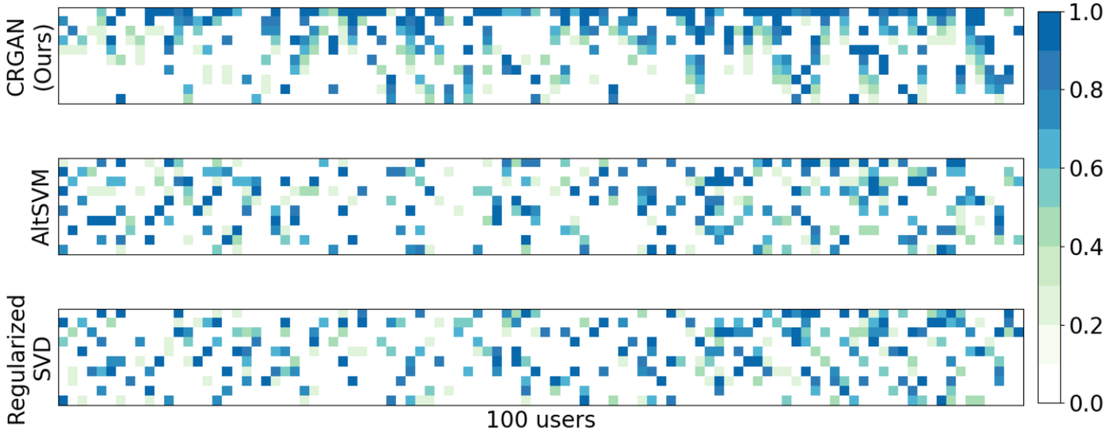
	HR@10↑	P@10↑	NDCG@10↑	AUC@10↑	MAP@10↑	MRR@10↑
IRGAN	0.9309	0.3425	0.3632	0.7290	0.3623	0.1341
MLP	0.9439	0.3489	0.3832	0.7353	0.3763	0.1431
GMF	0.9342	0.3503	0.3837	0.7327	0.3770	0.1432
NeuMF	0.9469	0.3543	0.3964	0.7374	0.3863	0.1492
CoFiRank	0.8677	0.2799	0.3054	0.6553	0.3060	0.1176
RegularizedSVD	0.8946	0.3333	0.3588	0.7371	0.3624	0.1343
RankBasedSVD	0.9530	0.3510	0.3945	0.7324	0.3855	0.1494
LCR	0.9543	0.3524	0.3953	0.7280	0.3847	0.1491
Primal-CR	0.9030	0.3289	0.3512	0.7048	0.3520	0.1318
Primal-CR++	0.9027	0.3295	0.3507	0.7050	0.3515	0.1314
AltSVM	0.9518	0.3641	0.3972	0.7393	0.3860	0.1468
Global Ranking	0.9523	0.3549	0.3985	0.7390	0.3895	0.1505
CRGAN(ours)	0.9820	0.4488	0.4697	0.7613	0.4509	0.1632

MovieLens1M

	HR@10↑	P@10↑	NDCG@10↑	AUC@10↑	MAP@10↑	MRR@10↑
IRGAN	0.9575	0.2859	0.3106	0.6374	0.3210	0.1244
MLP	0.9673	0.2982	0.3195	0.6683	0.3346	0.1270
GMF	0.9465	0.2603	0.2756	0.6223	0.2956	0.1123
NeuMF	0.9642	0.2884	0.3060	0.6598	0.3234	0.1221
CoFiRank	0.9499	0.2604	0.2737	0.6310	0.2964	0.1118
RegularizedSVD	0.9754	0.3185	0.3406	0.6937	0.3548	0.1335
RankBasedSVD	0.9510	0.2764	0.3033	0.6455	0.3198	0.1237
LCR	0.9549	0.2781	0.3066	0.6310	0.3168	0.1243
Primal-CR	0.9475	0.2798	0.3015	0.6472	0.3213	0.1219
Primal-CR++	0.9471	0.2797	0.3015	0.6471	0.3213	0.1219
AltSVM	0.9654	0.3041	0.3292	0.6781	0.3452	0.1311
Global Ranking	0.9690	0.2998	0.3249	0.6732	0.3404	0.1298
CRGAN(ours)	0.9890	0.3833	0.4100	0.6953	0.4011	0.1511

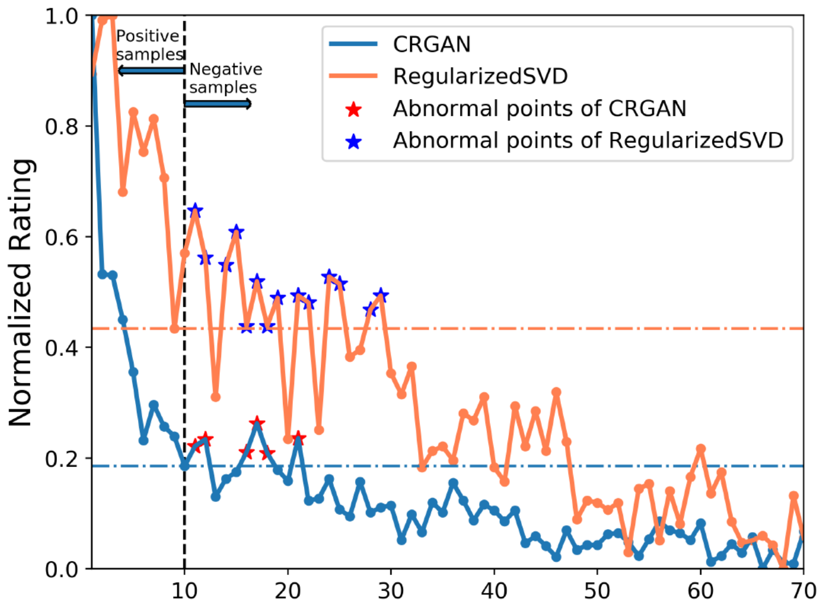
Netflix

Results



- Visualization of ranking results for the top-10 test items on Netflix. The grid with a deeper color represents a higher prediction score.
- Obviously, our method obtains more grids with deep colors, and they tend to hit the top half of the figure.

- Normalized rating for test items on Netflix. The score is monotonically decreasing $w.r.t.$ the true ranking.
- The curve of CRGAN is much smoother than RegularizedSVD, especially in the positive sample area.
- Moreover, there are less abnormal points that locate in negative sample area for our framework, which are predicted higher than some positive samples.



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Conclusion

- Our work focuses on collaborative ranking under the pairwise comparison setting.
- In our adversarial framework, two agents paly a minimax game:
  - A deep generator learning non-linear score function
  - A discriminator providing stricter supervision signals
  - When the game reaches equilibrium, the ranking results based on the learned scores could be consistent with the preference.
- Further analysis shows that our framework is generic.
- The experimental results also confirm its superiority.

THANKS!

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