Fairly Recommending with Social Attributes: A Flexible and Controllable Optimization Approach

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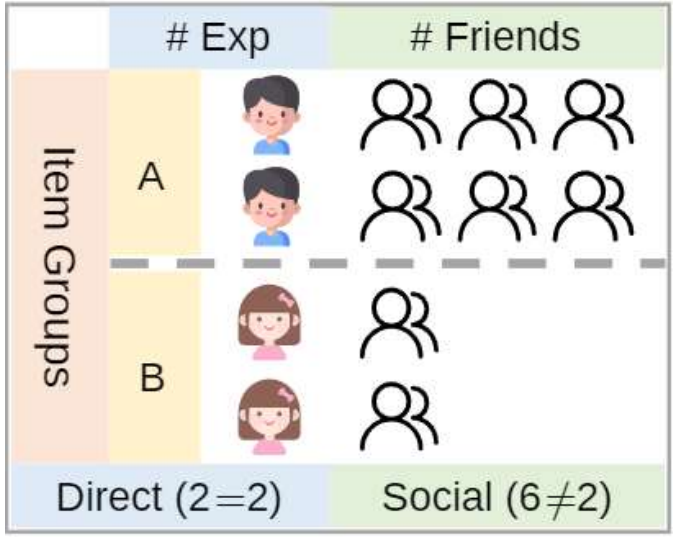
Background & Motivation (Part 1)

Item-side Group Fairness (IGF) in recommendation:

- It requires the model to **treat different item groups similarly**
- Existing IGF notions focus on the **direct utility** of item exposures

However, they overlook the user's **social utility**!

- Recommending items to users with **different social influence** may produce **varying utilities**.

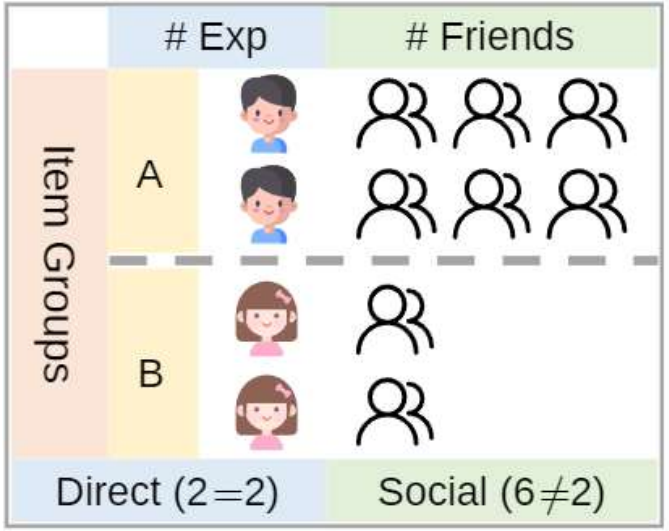


(a) Previous IGF notions

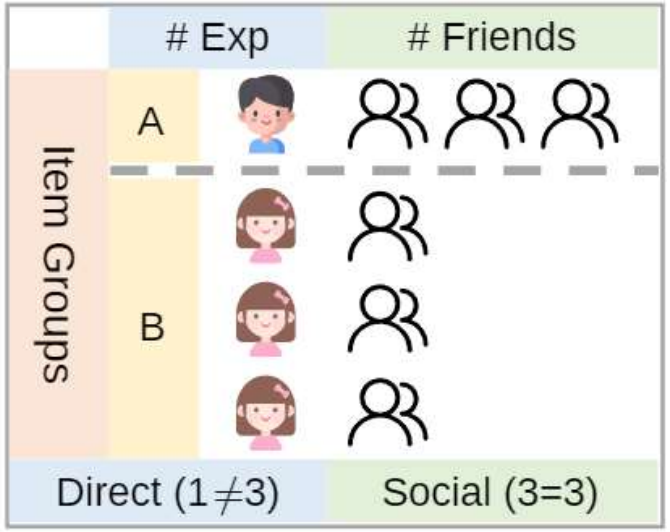
Background & Motivation (Part 2)

We thus introduce **social attribute-aware IGF** metrics.

- Users exposed to different item groups should have **similar social utility**.
- For example, the **number of friends** of exposed users…



(a) Previous IGF notions

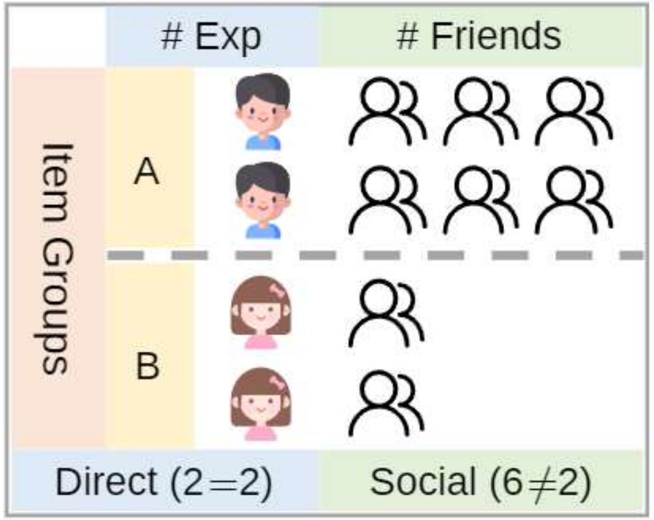


(b) Social attribute-aware notions

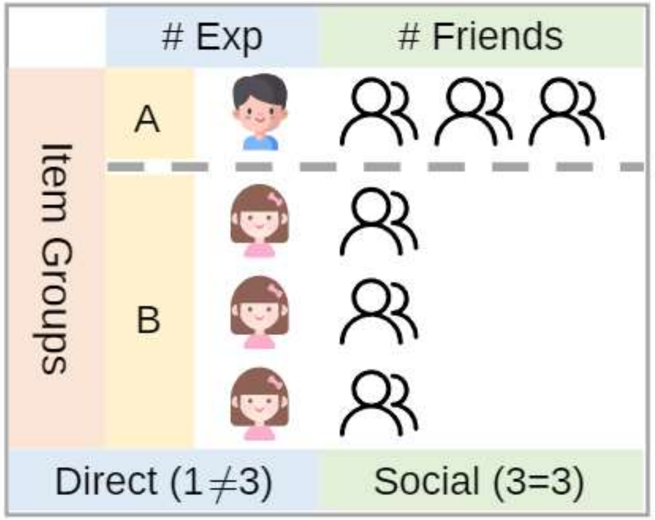
Background & Motivation (Part 3)

However, optimizing only social metrics may result in **varying direct** utilities!

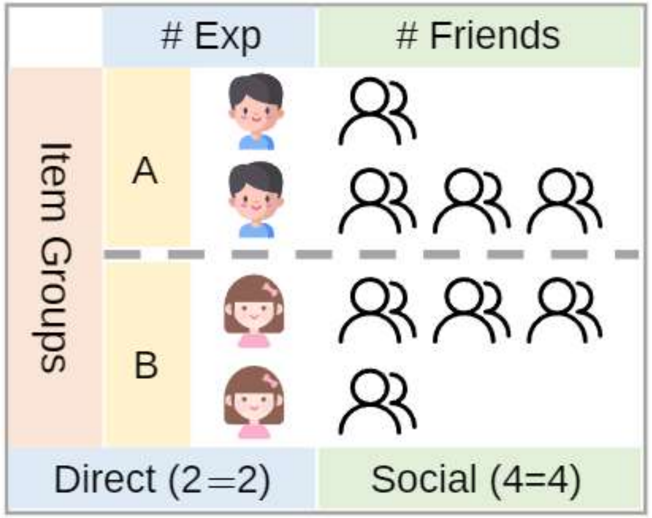
- We thus formulate a **multi-objective optimization problem**.
- **Flexible IGF trade-offs** & **Controllable recommendation accuracy**



(a) Previous IGF notions



(b) Social attribute-aware notions



(c) Multi-objective optimization

Social Attributes-Aware IGF

Neighborhood Statistical Parity (NSP):

sum of utilities from social network
(only difference with SP/EO!)

$$\mathrm{NR}\left(g=g_a\right)=\frac{\sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} G_{g_a}(i) \cdot \hat{Y}(u, i) \boxed{\sum_{v \in \mathcal{N}_u} R_v(i)}}{\sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} G_{g_a}(i)}, \quad \text{for all} \quad a=1, \cdots, A,$$

- Equal **"socially weighted"** likelihood of being recommended

Neighborhood Equal Opportunity (NEO):

$$\mathrm{NR}\left(g=g_a, y=1\right)=\frac{\sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} G_{g_a}(i) \cdot Y(u, i) \cdot \hat{Y}(u, i) \boxed{\sum_{v \in \mathcal{N}_u} R_v(i)}}{\sum_{u \in \mathcal{U}} \sum_{i \in \mathcal{I}} G_{g_a}(i) \cdot Y(u, i)}, \quad \text{for all} \quad a=1, \cdots, A,$$

- Equal **"socially weighted"** true positive rate (TPR)

Evaluation:

$$\begin{aligned} \mathrm{NSP} &= \operatorname{rsd}\left(\mathrm{NR}\left(g=g_1\right), \cdots, \mathrm{NR}\left(g=g_A\right)\right), \\ \mathrm{NEO} &= \operatorname{rsd}\left(\mathrm{NR}\left(g=g_1, y=1\right), \cdots, \mathrm{NR}\left(g=g_A, y=1\right)\right). \end{aligned}$$

Multi-Objective Optimization Problem Formulation

Formulated as:

$$\min_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}) = \left(\mathcal{L}_1(\boldsymbol{\theta}), \mathcal{L}_2(\boldsymbol{\theta}), \cdots, \mathcal{L}_M(\boldsymbol{\theta})\right)^{\mathrm{T}} \quad ①$$

$$s.t.\ \mathcal{G}_j(\boldsymbol{\theta}) = (\boldsymbol{s}_j - \boldsymbol{s}_n)^T \mathcal{L}(\boldsymbol{\theta}) \leq 0,\ \forall j = 1, \cdots, N, \quad ②$$

$$\mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}) \leq \xi. \quad ③$$

① Each $\mathcal{L}_i(\boldsymbol{\theta})$ takes from {SP, EO, NSP, NEO}; M is the number of objective.

② Ensure solutions fall within the **preference region**, where $\{s_j \in R_+^M\}$ is a set of **pre-defined unit vectors** to control **trade-offs** among IGF objectives.

③ Penalize instances with **accuracy loss** exceeding the **threshold**.

Reference: Lin X, Zhen H L, Li Z, et al. Pareto Multi-Task Learning[J]. In *Advances in Neural Information Processing Systems*, 2019.

Solving the Problem (Part 1)

Social-Aware **F**lexible Fair Recommendation with Controllable **A**ccuracy **(SoFA)**

Step 1: **Finding the initial solution**.

- Define $I_\epsilon(\boldsymbol{\theta}_r) = \{j = 1, \cdots, N \mid \mathcal{G}_j(\boldsymbol{\theta}_r) \geq -\epsilon\}$ (indices violating region constraints)
- Solve the problem: $(\boldsymbol{d}_r, \alpha_r) = \arg\min_{\boldsymbol{d}, \alpha \in R} \alpha + \frac{1}{2}\|\boldsymbol{d}\|^2, \ s.t. \ \nabla\mathcal{G}_j(\boldsymbol{\theta}_r)^T \boldsymbol{d} \leq \alpha, \ j \in I_\epsilon(\boldsymbol{\theta}_r).$
- Gradient-based update: $\boldsymbol{\theta}_{r_{t+1}} = \boldsymbol{\theta}_{r_t} + \eta_r \boldsymbol{d}_{r_t}$

Step 2: **Solving the Subproblem.**

- Compute $\boldsymbol{d}_t$ from $\boldsymbol{\theta}_t$ to $\boldsymbol{\theta}_{t+1}$ by solving:

$$
\begin{aligned}
(\boldsymbol{d}_t, \alpha_t) = & \arg\min_{\boldsymbol{d}, \alpha \in R} \alpha + \frac{1}{2}\|\boldsymbol{d}\|^2 \\
s.t. \ & \nabla\mathcal{L}_i(\boldsymbol{\theta}_t)^T \boldsymbol{d} \leq \alpha, \ i = 1, \cdots, M, \\
& \nabla\mathcal{G}_j(\boldsymbol{\theta}_t)^T \boldsymbol{d} \leq \alpha, \ j \in I_\epsilon(\boldsymbol{\theta}_t), \\
& \nabla\mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t)^T \boldsymbol{d} \leq \alpha, \ \text{if } \mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t) \geq \xi.
\end{aligned}
$$

Reference: Jörg Fliege and Benar Fux Svaiter. Steepest Descent Methods for Multicriteria Optimization. *Mathematical methods of operations research*, 51:479–494, 2000.

Solving the Problem (Part 2)

Dual Problem: $$\min_{\alpha_i,\beta_j,\lambda} \frac{1}{2}\left\|\sum_{i=1}^{M}\alpha_i\nabla_{\boldsymbol{\theta}_t}\mathcal{L}_i(\boldsymbol{\theta}_t)+\sum_{j\in I_\epsilon(\boldsymbol{\theta}_t)}\beta_j\nabla_{\boldsymbol{\theta}_t}\mathcal{G}_j(\boldsymbol{\theta}_t)+\lambda\cdot\mathbb{I}(\mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t)\geq\xi)\nabla_{\boldsymbol{\theta}_t}\mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t)\right\|^2$$

$$s.t.\ \sum_{i=1}^{M}\alpha_i+\sum_{j\in I_\epsilon(\boldsymbol{\theta}_t)}\beta_j+\lambda\cdot\mathbb{I}(\mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t)\geq\xi)=1,$$ (can be solved by MGDA)

According to **KKT conditions**, we have:

- If $\boldsymbol{\theta}_t$ is Pareto optimal, no direction simultaneously improves all objectives.
- Otherwise, $$\nabla\mathcal{L}_i(\boldsymbol{\theta}_t)^T\boldsymbol{d}^*\leq\alpha^*\leq-\|\boldsymbol{d}^*\|^2<0,\ i=1,\cdots,M,$$ $$\nabla\mathcal{G}_j(\boldsymbol{\theta}_t)^T\boldsymbol{d}^*\leq\alpha^*\leq-\|\boldsymbol{d}^*\|^2<0,\ j\in I_\epsilon(\boldsymbol{\theta}_t),$$ $$\nabla\mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t)^T\boldsymbol{d}^*\leq\alpha^*\leq-\|\boldsymbol{d}^*\|^2<0,\ \text{if } \mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t)\geq\xi,$$

$\boldsymbol{d}^*$ decreases all IGF losses & recommendation loss (when $\mathcal{L}_{\mathrm{BPR}}(\boldsymbol{\theta}_t)\geq\xi$).

Reference: Jean-Antoine Désidéri. Multiple-Gradient Descent Algorithm (MGDA) for Multiobjective Optimization. *Comptes Rendus Mathematique*, 350(5-6):313–318, 2012.

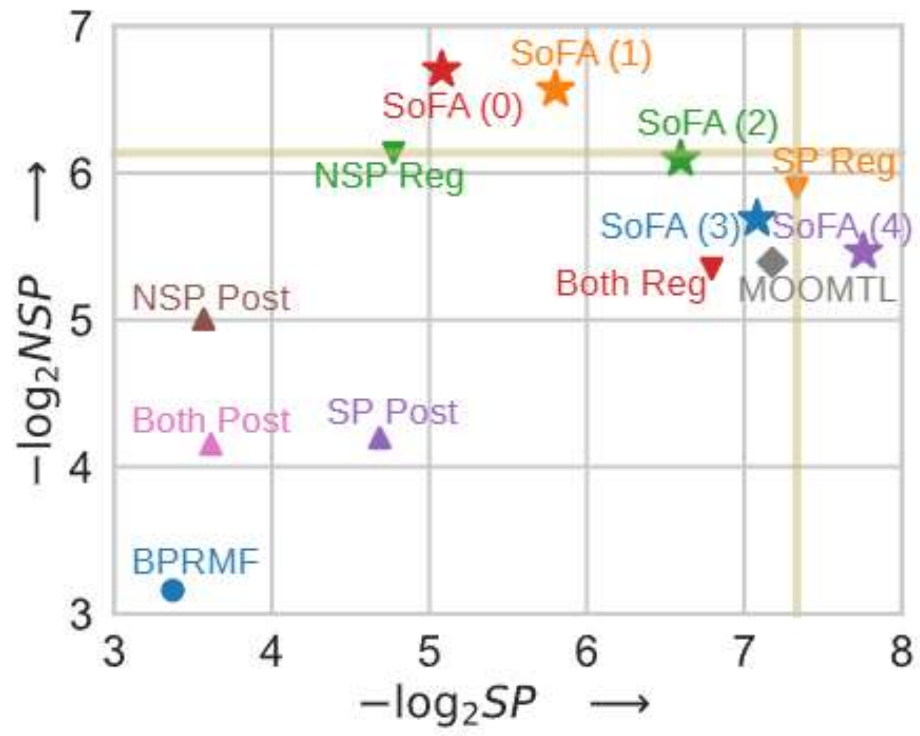
Experimental Results (Part 1)

Table 1: Performance comparison using SP and NSP as IGF notions, where SoFA is implemented with five preference regions. The best and second best results are bolded and underlined, respectively.

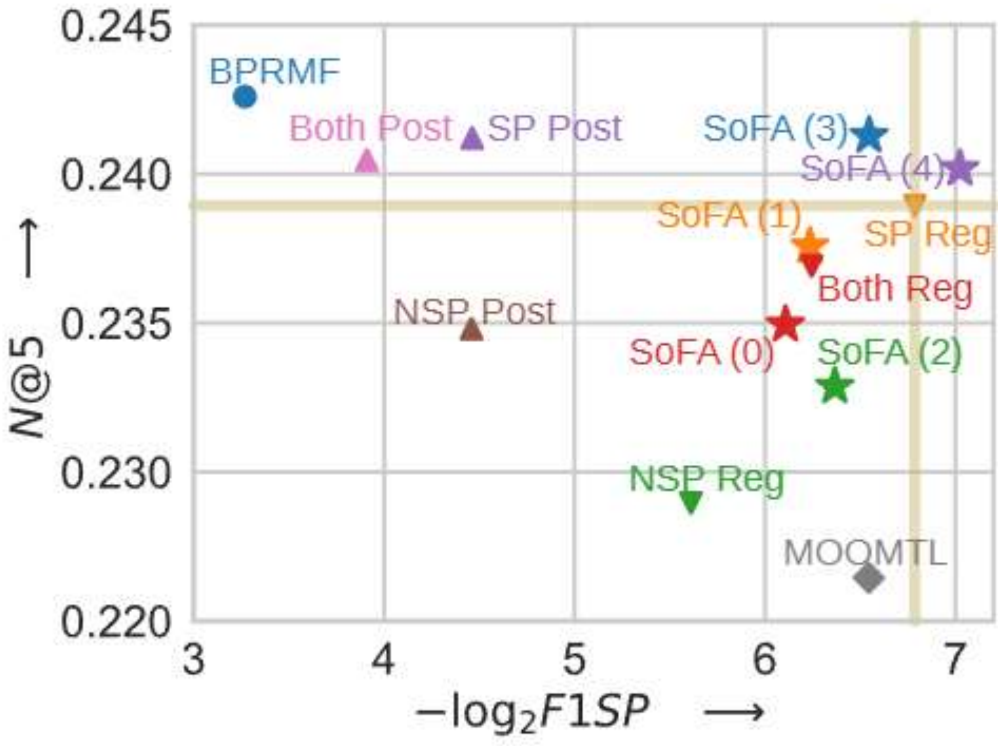
	KuaiRec				Epinions			
	N@5↑	SP↓	NSP↓	F1SP ↓ $_{deg}$	N@5↑	SP↓	NSP↓	F1SP↓ $_{deg}$
BPRMF	**0.2426**	0.0966	0.1119	0.1037 49.2°	0.0443	0.0252	0.0286	0.0268 48.6°
+ SP Reg	0.2389	0.0062	0.0168	0.0091 69.7°	0.0450	0.0140	0.0196	0.0163 54.5°
+ NSP Reg	0.2279	0.0366	0.0142	0.0205 21.2°	0.0378	0.0224	0.0188	0.0205 40.0°
+ SP&NSP Reg	0.2369	0.0090	0.0245	0.0132 69.8°	0.0448	0.0154	0.0205	0.0176 53.2°
+ SP Post	0.2412	0.0388	0.0545	0.0454 54.5°	0.0445	0.0141	0.0196	0.0164 54.2°
+ NSP Post	0.2348	0.0844	0.0311	0.0455 20.3°	0.0398	0.0212	0.0185	0.0197 41.2°
+ SP&NSP Post	0.2405	0.0817	0.0562	0.0666 34.5°	0.0443	0.0152	0.0207	0.0175 53.7°
MOOMTL	0.2229	0.0069	0.0238	0.0107 73.8°	0.0446	0.0138	0.0193	0.0161 54.4°
SoFA $_{\text{region 0}}$	0.2349	0.0296	**0.0096**	0.0145 18.0°	0.0364	0.0909	0.0294	0.0445 17.9°
SoFA $_{\text{region 1}}$	0.2376	0.0179	0.0105	0.0133 30.4°	0.0441	0.0326	0.0225	0.0266 34.6°
SoFA $_{\text{region 2}}$	0.2329	0.0103	0.0146	0.0121 54.8°	**0.0451**	0.0153	0.0210	0.0177 53.9°
SoFA $_{\text{region 3}}$	0.2413	0.0074	0.0194	0.0107 69.1°	0.0427	0.0118	**0.0177**	**0.0142** 56.3°
SoFA $_{\text{region 4}}$	0.2402	**0.0046**	0.0227	**0.0077** 78.5°	0.0185	**0.0095**	0.0314	0.0146 73.1°

Experimental Results (Part 2)

- Trade-offs between (a) IGF metrics, (b) fairness and accuracy on KuaiRec.



(a) SP and NSP trade-off



(b) F1SP and NDCG@5 trade-off

Conclusion

- We propose two **social attribute-aware IGF metrics**, named **NSP and NEO**, to study the item exposure utility gained from user social network.
- We formalize a **multi-objective optimization problem** to achieve **flexible trade-off** between the direct and social utility with **controllable accuracy**.
- We propose an algorithm called **SoFA** to solve the problem, **theoretically** show its ability to find **Pareto optimal solutions** with varying trade-offs.
- We conduct **extensive experiments** on two real-world datasets, validating the **effectiveness** of our proposal.