User Welfare Optimization in Recommender Systems with Competing Content Creators

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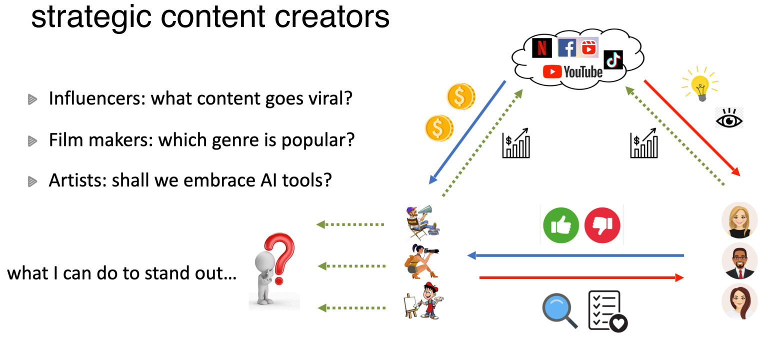
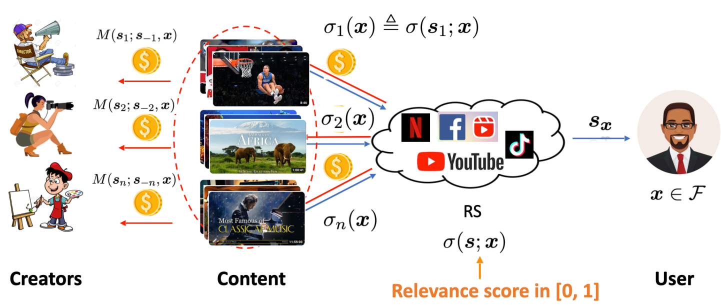
Problem Formulation & Motivation

- Rapidly growing content sharing platforms and strategic content creators



- Competing Content Creation (C^3) Game



- For each user x, platform measures the relevance score of each candidate content, and observes users feedback
- Platform incentives creators using designed reward function M. Creators are involved in a game and they optimize their utilities given by

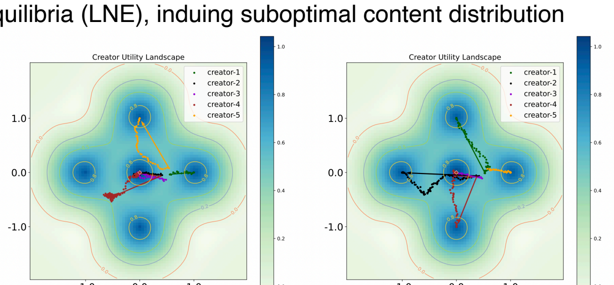
$$u_i(s_i, s_{-i}) = \mathbb{E}_{x \in \mathcal{F}}[M(s_i; s_{-i}, x)].$$

Key Assumption: (Myopic Creators) Creators update strategies with local better-response, i.e., an incremental update along a random direction that increases their utilities.

Research question: How to optimize user welfare

$$W(s) = \mathbb{E}_{x \in \mathcal{F}}[\sigma(s_x, x)].$$

- Challenge brought by creator's strategic behaviors
  - Due to myopic behavior incurred by insufficient knowledge about user preference distribution, creators can stuck at local Nash equilibria (LNE), induing suboptimal content distribution



Suboptimal distribution at LNE   Optimal distribution at NE

Theoretical Results

- A popular baseline — engagement-based reward

Post-Matching Reward   Matching Probability

$$M(s_i; s_{-i}, x) = \boxed{R(s_i, x)} \cdot \boxed{P_i([s_1, \cdots, s_n], x)}$$
$$\propto \boxed{\sigma_i(x)} \cdot \boxed{\mathrm{Softmax}_i([\beta^{-1}\sigma_{l(k)}(x)]_{k=1}^{K})}$$

Index of top-K ranked contents

- Previous work[Yao'23] showed such an incentive design leads to $\mathcal{O}\left(\frac{1}{\log K}\right)$ welfare loss, when creators adopt *no-regret learning.* *However, it can be even worse when creators are myopic!*

- Proposed solution: User importance reweighing (UIR)

$$M(s_i; s_{-i}, x) = R(s_i, x) \cdot P_i([s_1, \cdots, s_n], x)$$
$$\propto w(x)\sigma_i(x) \cdot \mathrm{Softmax}_i([\beta^{-1}\sigma_{l(k)}(x)]_{k=1}^{K})$$

- Platform assigns different weights w to different users groups
- use w to adjust the payment to creators
- adaptively update w to steer the creators' evolving strategies:

$$w^{(t+1)}(s) \propto w^{(t)}(s) \cdot \exp\left(-\alpha \boxed{\bar{\pi}^{(t)}(s)}\right)$$

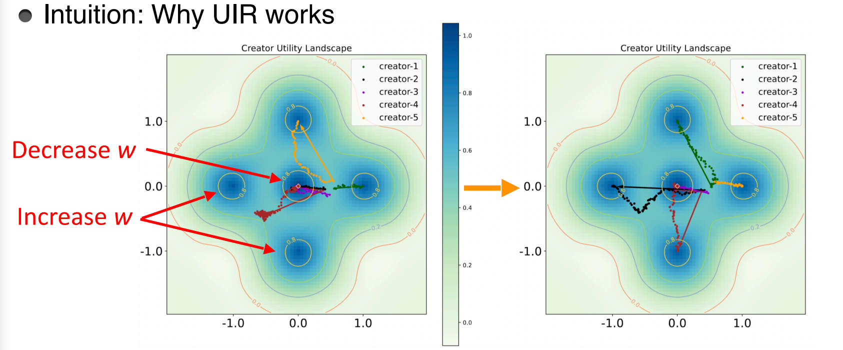
Current avg. utility of each user group

Theorem [Informal] When the number of creators is sufficiently large and the user population is well separated, the following update

$$w'_j = w_j \cdot e^{-\eta \bar{\pi}(x_j)}, \forall j \in [m],$$

improves the user welfare at any LNE s, where $\bar{\pi}(x_j)$ is the expected utility of user x_j at s.

- Intuition: Why UIR works



- Alternative intervention mechanisms:
  If payment is not feasible, simply adjust matching probability P
  - Soft Matching Truncation (SMT)

$$R(s_i, x) \propto \sigma_i(x), \quad P_i([s_1, \cdots, s_n], x) = \mathrm{Softmax}_i([\beta^{-1}(w(x))\sigma_{l(k)}(x)]_{k=1}^{K}).$$

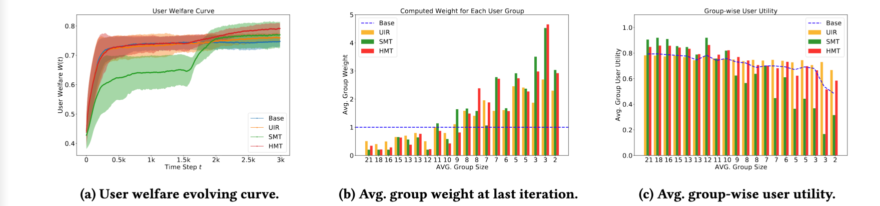
  - Hard Matching Truncation (HMT)

$$R(s_i, x) \propto \sigma_i(x), \quad P_i([s_1, \cdots, s_n], x) = \mathrm{Softmax}_i([\beta^{-1}\sigma_{l(k)}(x)]_{k=1}^{K(w(x))}).$$

Same idea as UIR: increasing the chance of exposure for underserved user groups!

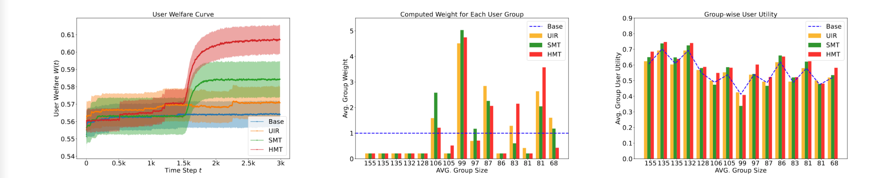
Experiments

- Offline experiments on synthetic and MovieLens data



(a) User welfare evolving curve.   (b) Avg. group weight at last iteration.   (c) Avg. group-wise user utility.

Figure 2: Performance of UIR, SMT and HMT on synthetic dataset against the no-intervention baseline. Results are averaged over 10 independently sampled synthetic environments including one-sigma error bars. x-axis: group sizes divided by 10.



(a) User welfare evolving curve.   (b) Avg. group weight at last iteration.   (c) Avg. group-wise user utility.

Figure 3: Performance of UIR, SMT and HMT on MovieLens-1m dataset against the no-intervention baseline. Results are averaged over 10 independent simulations including 0.2-sigma error bars.

- Online experiment on Instagram Reels of 3 weeks
  - welfare metric: like-through-rate
  - Symmetric A/B test: exclusively pair 3% creators with 3% users from the entire platform
  - Cluster users into 10k groups by multiple characteristics
    - Demographics: country, gender, race, occupation, etc.
    - Level of activeness: video consumption volume and watch time

User Groups	1-5	6-20	21-74	75+	TOTAL
Like-Through-Rate	+0.43%	+1.40%	+0.75%	+1.36%	**+1.13%**
Impression	+2.64%	+0.62%	+1.42%	+0.11%	**+0.76%**

- ☑ *3.7%* increase in impressions on fresh content created within 2 hours
- ☑ Average number of consumed topic per user increased by ***0.71***
- ☑ An increasing trend of daily active creators
  - ☑ Head creators increased by 0.17%, others increased by 0.06%
  - ☑ 0.48% increase in the third week of experiment period

☆ *User engagement*
☆ *Content creation volume/diversity*

Summary and Takeaway

- *A game-theoretical **FRAMEWORK** to model content creation dynamics.*
- *Establish **THEORY** that guides the platform to steer creators' behavior towards a content distribution better aligned with user preferences.*
- *Propose **practical solutions** that deliver promising results for ~10 millions of users and creators in real traffics!*