full paper



The Disparate Effects of Recommending to Strategic Users

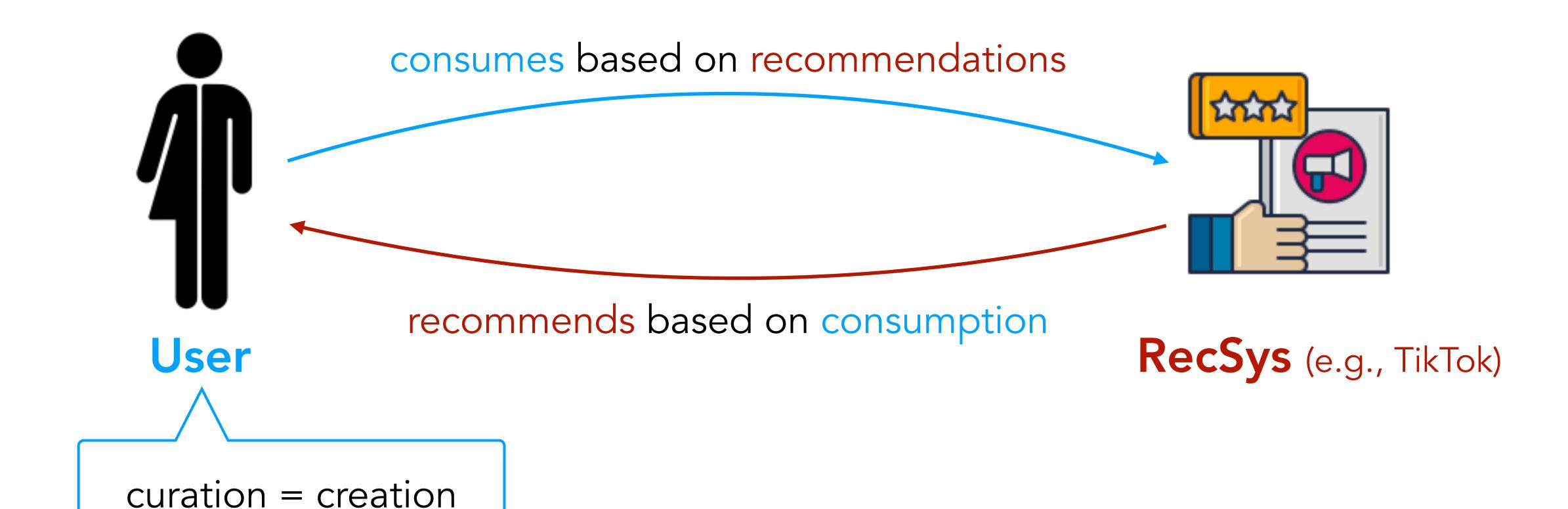
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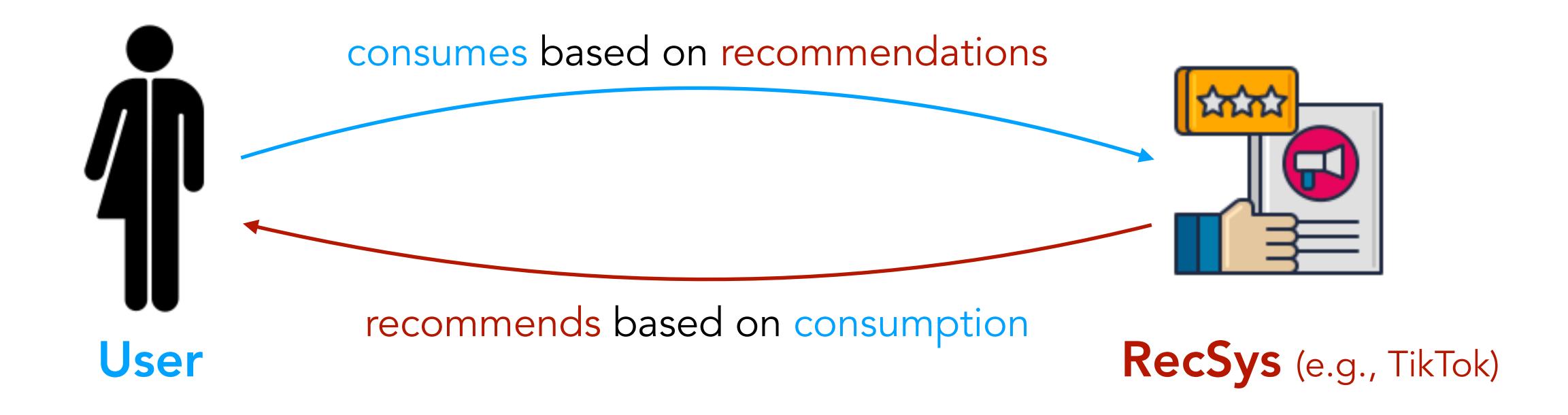




RecSys create a feedback loop

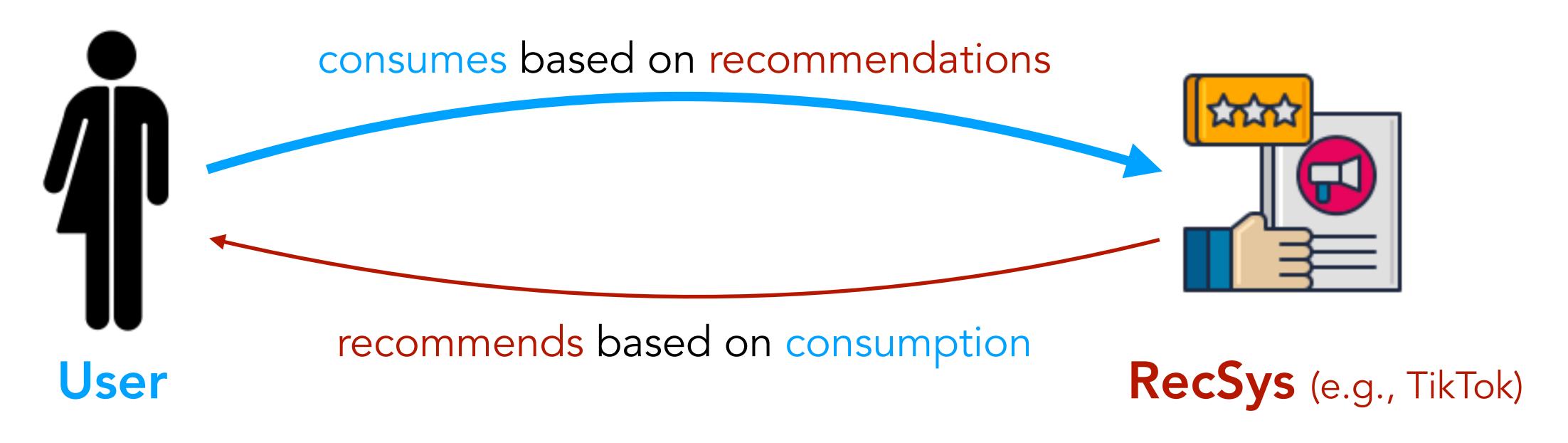


Main Questions



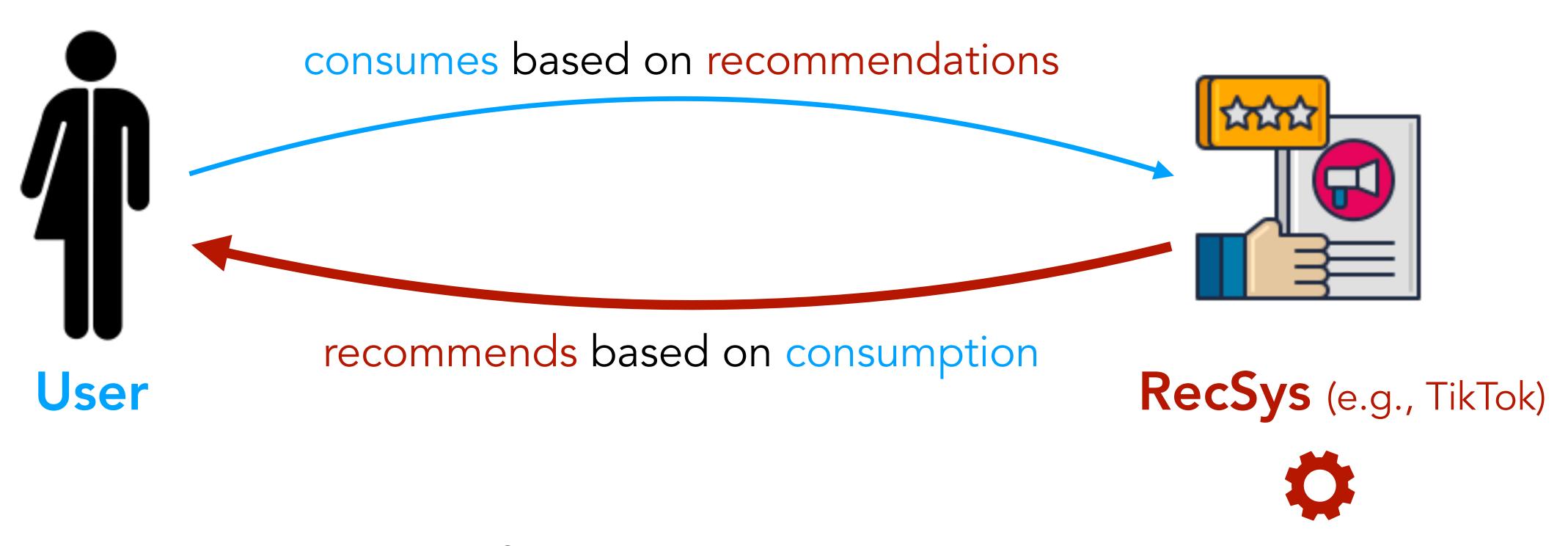
Main Questions

1: Are users aware of feedback loop? Do they act in response?



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Q2: Harms to users if RecSys does not adapt? Interventions?

Contributions

Q1: Are users aware of feedback loop? Do they act in response?

Survey on user consumption patterns on TikTok.



- Introduction of theoretical model about recommending to strategic agents.
- Disparate impact for minority in equilibrium (proof of concept).

 Q2: Harms to users if RecSys does not adapt? Interventions?

Survey on TikTok consumption

- * Survey on MTurk 12/22 01/23 (100 participants)
- * Mostly free-form text responses \rightarrow qualitative data analysis

Why do you think TikTok recommends these categories?

"I feel that TikTok continues to put these in my feed because I almost always get sucked into watching them. That **tells the algorithm I like them**, even though I am mostly **just using them for background noise** and have seen most of them before"



"I think because I liked a video once of this type of content. I believe by me liking the video the algorithm thought I would like to see more videos like that one."

Actions you take to curate your feed?

"I also like stuff just to see more of that type stuff evn though I don't like it. Llke soemtimes if my content gets to dark I try to like animal videos and comedy more to get off the darker content for a bit." [sic]

Positive Association Curation Curation Curation Curation Categoritation Curation Coding

"I also my content of the positive Association Coding "Curation Coding"

"Curation Coding"

"Currently, I am cognizant of what category of video I think material falls under. I am careful to watch completely videos that fall under the correct category (even if I am not interested in that particular video). I am careful to skip over videos from the "wrong" categories."





Contributions

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Model: Strategic Recommendation as a Stackelberg Game

Players

Leader: RS



Follower: *User*



Timeline of play

RS commits to a **strategy**

g. Users observe g.

Exploration phase

(Cold Start)

Exploitation phase

(Recommendation)

time

RS randomly presents contents to users







Users consume

content ~ preferences + strategy

From consumption pattern, *RS* infers user type (e.g., sporty spice).

RS implements **policy** g to **map** inferred type to recommended content



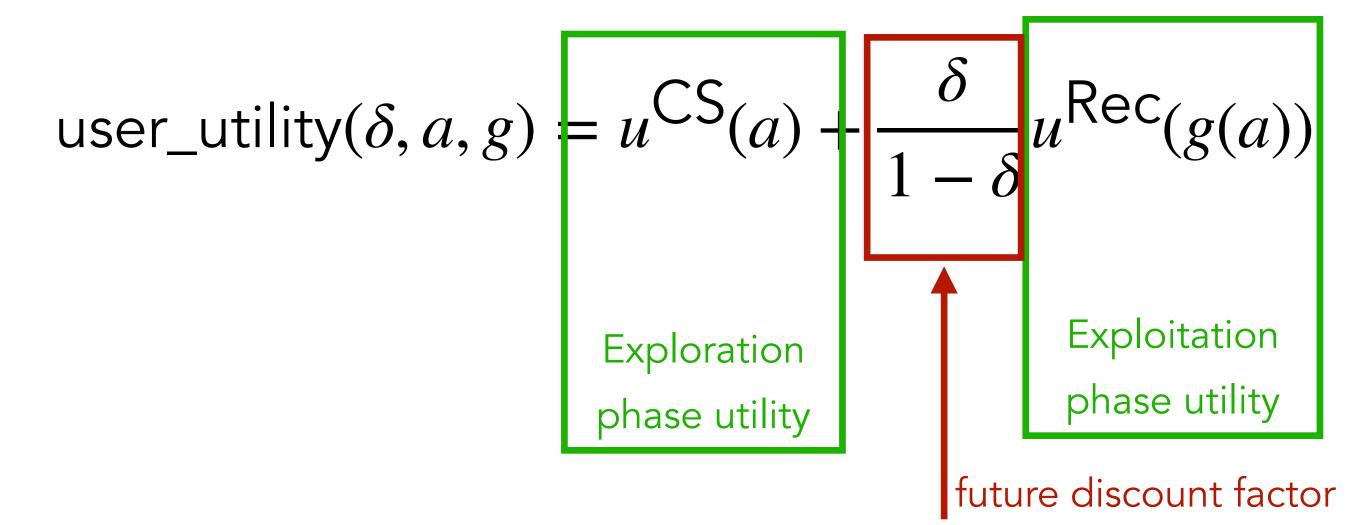
Model: Strategic Recommendation

How does RS choose the recommendation policy g?

Exploration phase data at face value \rightarrow choose g to max welfare

How does the *User* choose the consumption plan a?

 $\Big({\sf consumption} \sim {\sf Poisson}({\sf exposure_rate} \cdot {\sf consumption_plan}) \Big)$



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 Sources:
 - i cognitive burden i utility under strategizing vs under truthtelling

Disparate impact

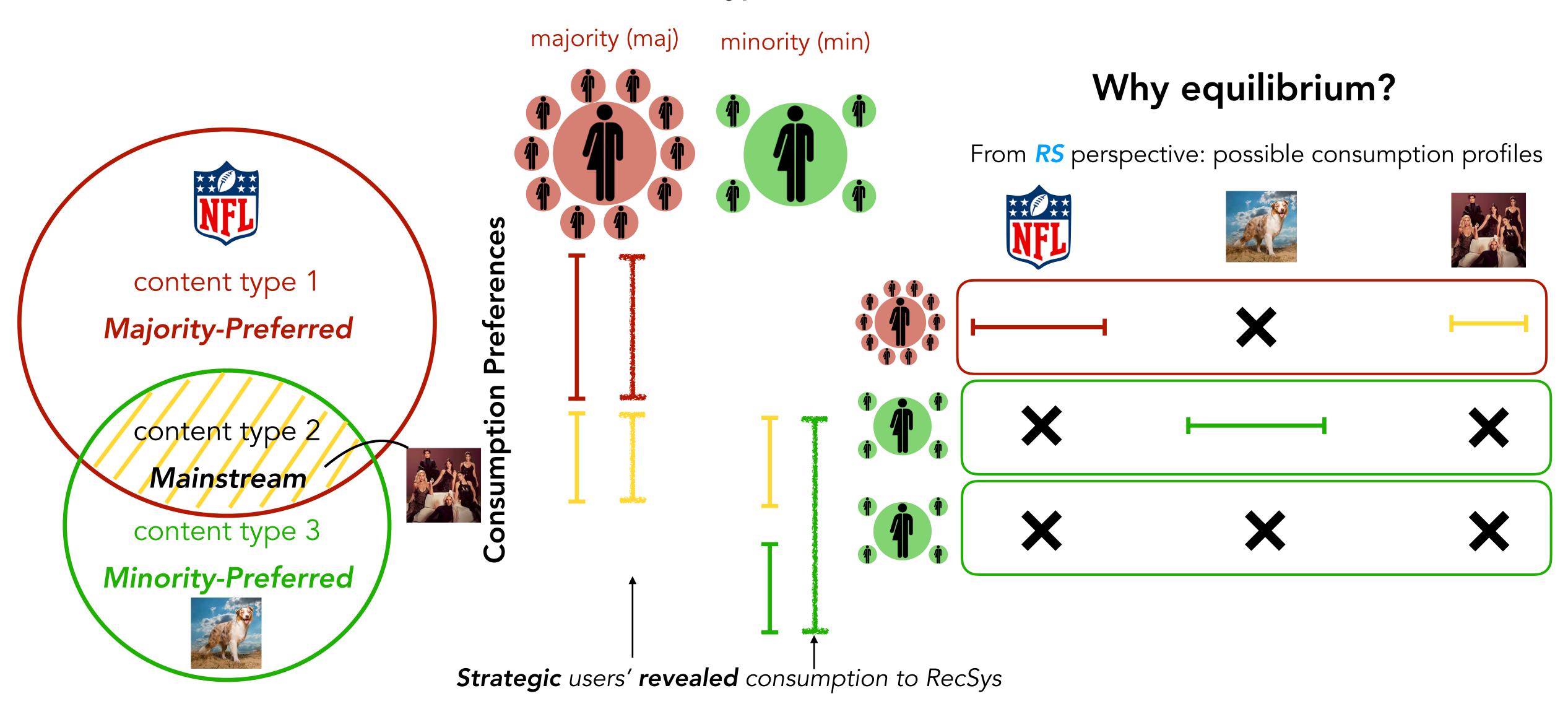
User Types

RecSys equilibrium:

Else, maj-pref.

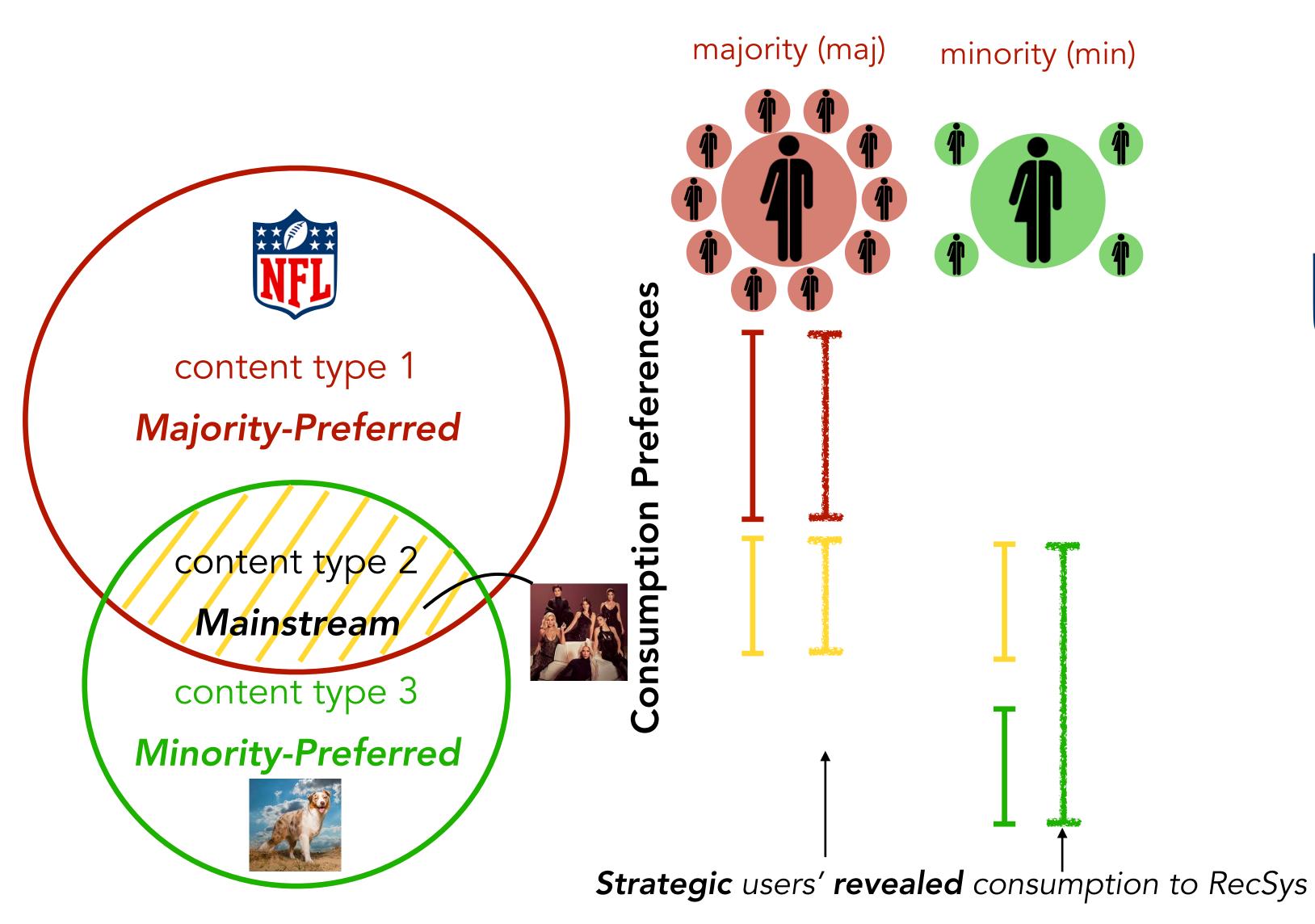
Recommend min-pref, if no preference for

content type 1, 2 or some preference for type 3.



Disparate impact

User Types

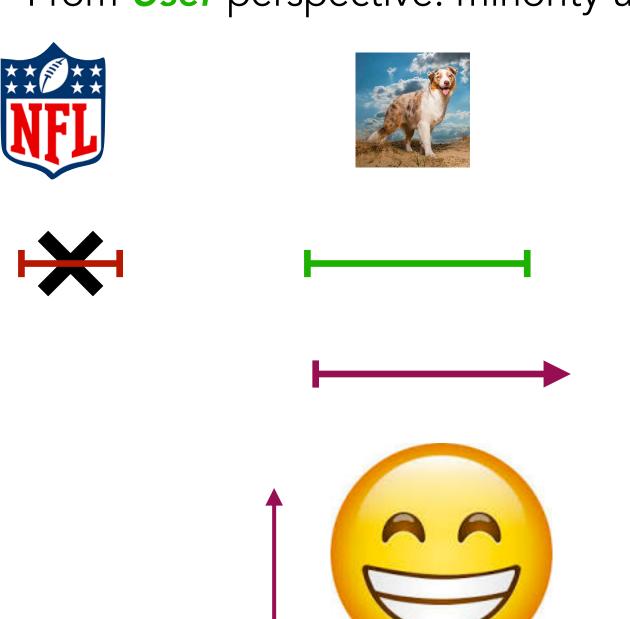


RecSys equilibrium:

- Recommend min-pref, if no preference for content type 1, 2 or some preference for type 3.
- Else, maj-pref.

Why equilibrium?

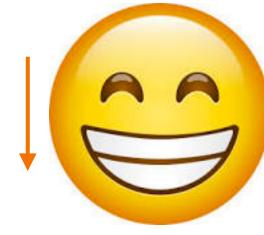
From *User* perspective: minority user utility





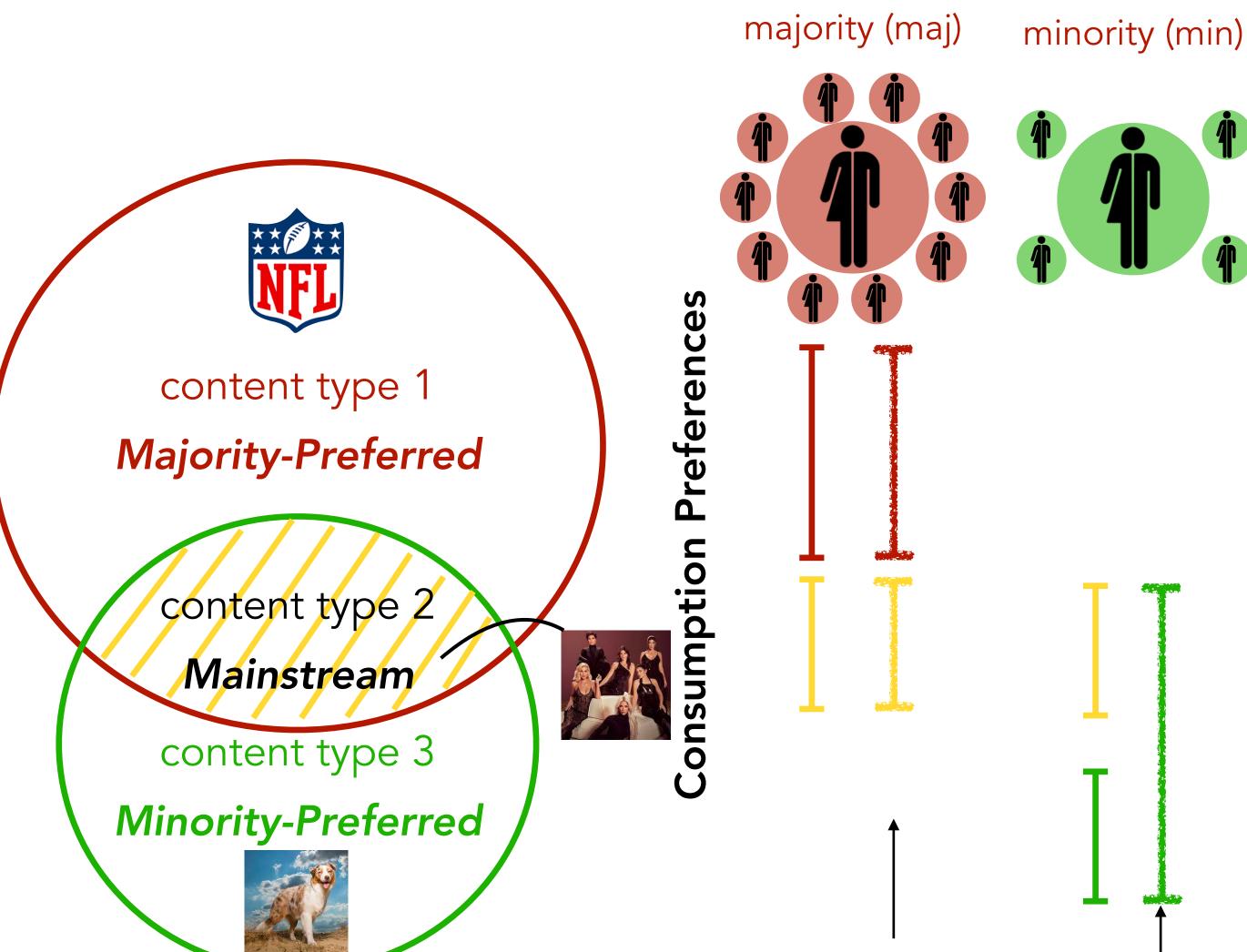






Disparate impact

User Types



RecSys equilibrium:

- * Recommend min-pref, if no preference for content type 1, 2 or some preference for type 3.
- * Else, maj-pref.

Implications for Minority

- 1) maj users: no need to strategize!
- 2) min users: act more stereotypically
- 3) min users: mainstream abstention

"I make sure to interact things that are specific to content types I want to see, even if I don't really like the content of that specific video."

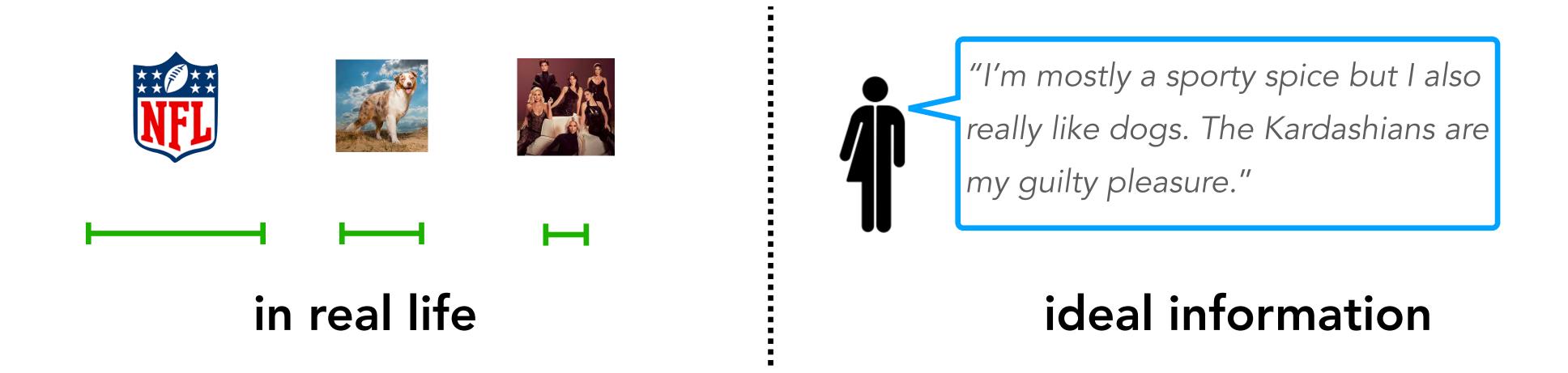
"I would use that to search things that I wouldn't want recommended to me. Stuff that I like, but stuff that I wouldn't want to clog my feed."

Strategic users' **revealed** consumption to RecSys



Fundamental problem in recommending to strategic users

RS has imperfect, coarse information wrt user type.



Interventions guiding principle: fine tune learning priorities wrt user type inference

Open Questions / Directions

1. Understanding platforms' awareness of individuals' incentives.

2. Modeling incentives and system dynamics for content creators.

3. Understanding the Price of Personalization in RecSys.

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Q2: Harms to users if RecSys does not adapt? Intervention

Survey on user consumption patterns on TikTok.



Thank You!

- Disparate impact for minority in equilibrium (proof of concept).

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Understanding user utility

$$u_U(q, x, a; \theta) = u^{CS}(q, a; \theta) + u^{Rec}(x; \theta)$$

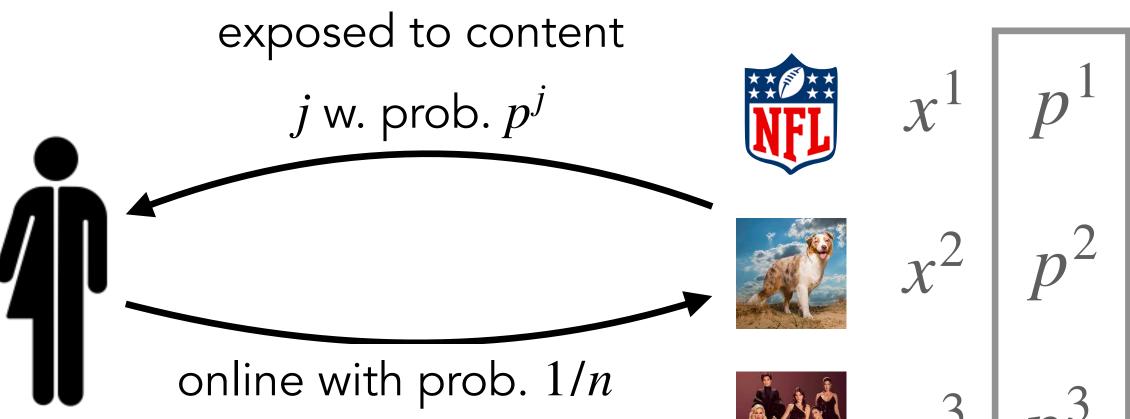
$$\approx \theta^j = \Pr[\text{like content } j]$$

During the Cold Start Phase (assume duration n rounds)...

exposure probabilities (chosen independently from RecSys)

3 factors affecting user utility at **Cold Start**

- 1. exposure rates: p^{J}
- 2. round interaction: 1/n
- 3. consumption plan: a^{j}



plan to consume with prob. a^{j}

$$q^{j} \sim \pi(a^{j}) = Pois(p^{j}a^{j})$$

- If $a^j \le \theta^j \Rightarrow$ consume only q^j & get utility $q^j \cdot 1$
- ii) If $a^j > \theta^j \Rightarrow \Pr[\text{like } j \mid \text{consume } j] = \theta^j/a^j$. Utility $= q^j \cdot \left(1 \cdot \frac{\theta^j}{a^j}\right) + (-1) \cdot \left(1 \frac{\theta^j}{a^j}\right)$ $u^{CS} = \sum_{j \in [d]} p^j (2 \min\{\theta^j, a^j\} a^j)$

$$u^{CS} = \sum_{j \in [d]} p^{j} (2 \min\{\theta^{j}, a^{j}\} - a^{j})$$

Interventions

1. Recommendation choice intervention: over-representing minorities.

2. Information design intervention: automatic incognito mode.

Would your behavior on TikTok change in an incognito mode that does not log responses?

Incognito Mode Coding	Participant Count
no change: no reason	45
no change: less personalization	14
change: click "avoided" content	10
change: click "feed-clogging" content	9
change: exploration increase	9
other	8

Interventions

1. Recommendation choice intervention: over-representing minorities.

2. Information design intervention: automatic incognito mode.

3. Information gathering intervention: Cold Start improvement