Supply-Side Equilibria in Recommender Systems

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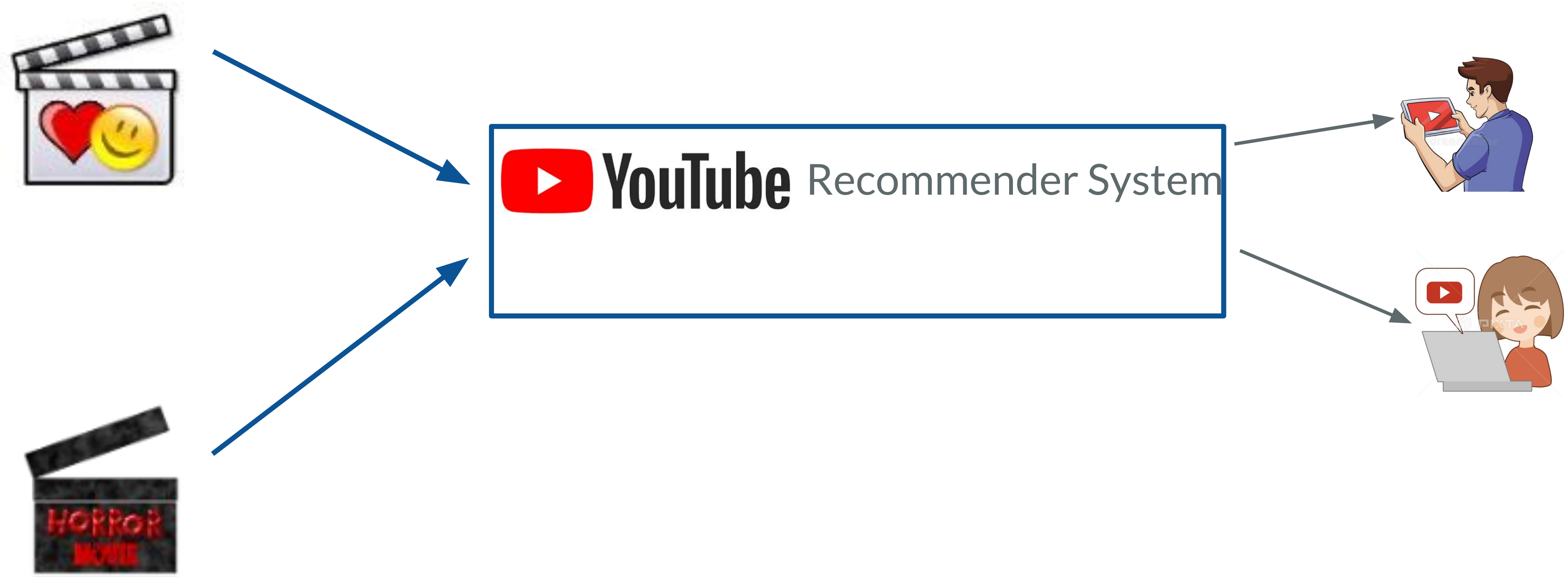
Joint work with Nikhil Garg (Cornell Tech) and Jacob Steinhardt (UC Berkeley)

Content recommendation as an isolated system



Reality: Content recommendation in a marketplace

YouTube Recommender System

Content producers compete to be recommended to users.

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Strategically create content that optimizes for recommendations

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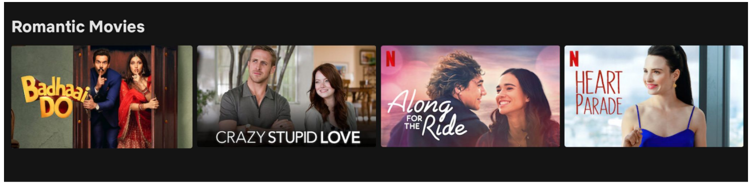
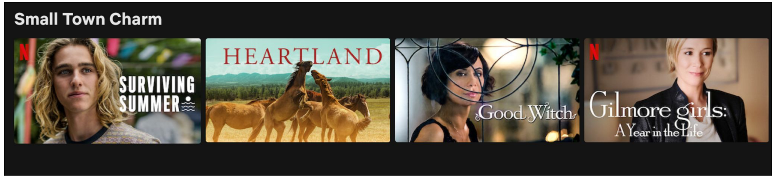
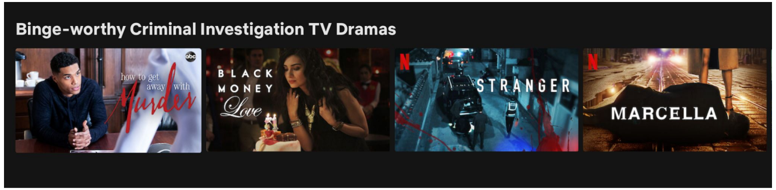
<u>This paper</u>: impact of recommender system on **content created at equilibrium**

How personalized recommendations impact producers







Niche content can reach the right audience!

But some niche content may only appeal to a small set of users.

Producers may be incentivized to either:

1. Create specialized content catered to a subpopulation.
2. Create mainstream content catered to the “average” user.

Main question

When do personalized recommendations lead to specialization?

Main contributions

1. We propose a high-dimensional model for content creator competition in personalized recommender systems.

2. We theoretically characterize when specialization occurs.

3. We empirically study the role of the platform's algorithm.

Overview of our model

$j^*(u) \in \{1, 2, .. P\}$

$p_1 \in \mathbf{R}^d$ 

$p_2 \in \mathbf{R}^d$ 

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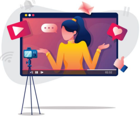
$p_P \in \mathbf{R}^d$ 

Algorithm

 $u_1 \in \mathbf{R}^d$

 $u_2 \in \mathbf{R}^d$

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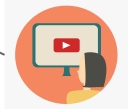 $u_N \in \mathbf{R}^d$

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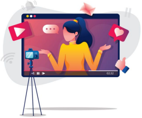

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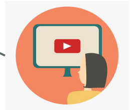

$u_N \in \mathbf{R}^d$

Each producer *selects* a D-dimensional content vector.

Overview of our model

Producer profit:

Fixed cost of
producing content

$$\mathbf{P}(p_j \mid p_{-j}, u_{1:N}) = \left(\sum_{1 \le i \le N} \mathrm{I}[j^*(u_i) = j]\right) - c(p_j)$$

Exposure (# of users won)

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$$c(p) = ||p||^{\beta}$$

***β* captures difficulty of excelling in many dimensions**

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Platform's recommendations:

$$j^*(u) = \operatorname{argmax}_{1 \leq j \leq P} \langle p_j, u \rangle$$

Linear score between p_j and u

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$$j^*(u) = \mathrm{argmax}_{1 \le j \le P} < p_j, u >$$

We study the symmetric mixed Nash equilibria of the game between producers.

Characterization of when specialization occurs

$|\mathrm{Genre}(\mu)| := \{\, p \,/\, ||p|| \;\; s.t.\; p \;\in \mathrm{supp}(\mu) \,\}$; μ exhibits specialization $\Leftrightarrow$ $|\mathrm{Genre}(\mu)| > 1$

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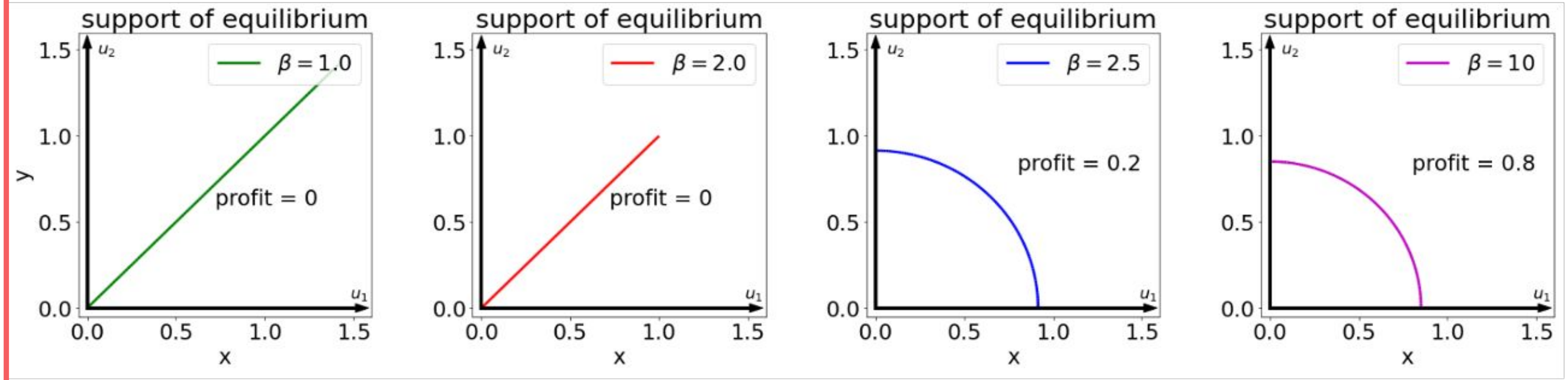
Example: $u_1 = [1, 0], u_2 = [0, 1]$ with $P = 2$ and cost function $c(p) = ||p||_2^{\beta}$



β ≤ 2: no specialization

β ≥ 2: specialization

Whether specialization occurs depends on producer costs + user embeddings.

Impact of platform's algorithm

Platform uses **nonnegative matrix factorization w/ D factors** to compute user embeddings $u_1, u_2, \ldots, u_N \in \mathbb{R}^D$.

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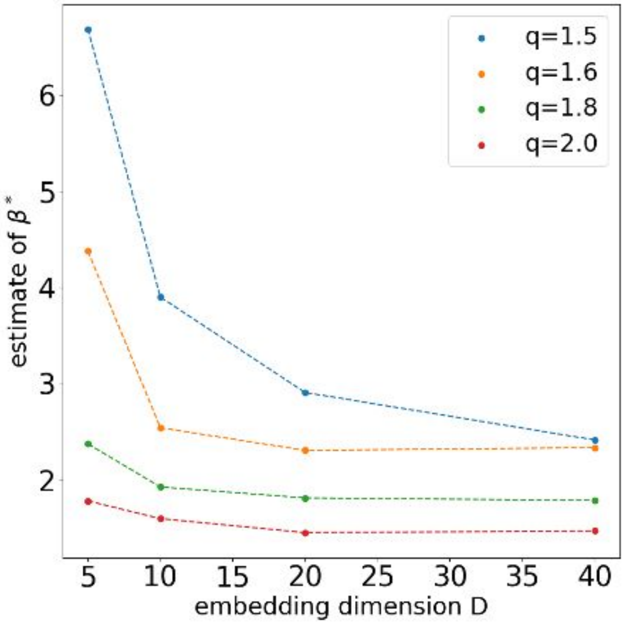
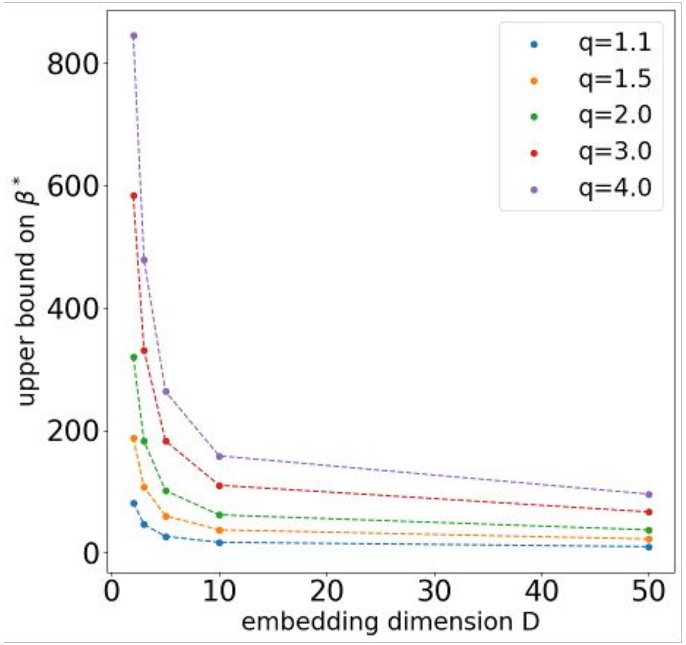




q = cost function norm

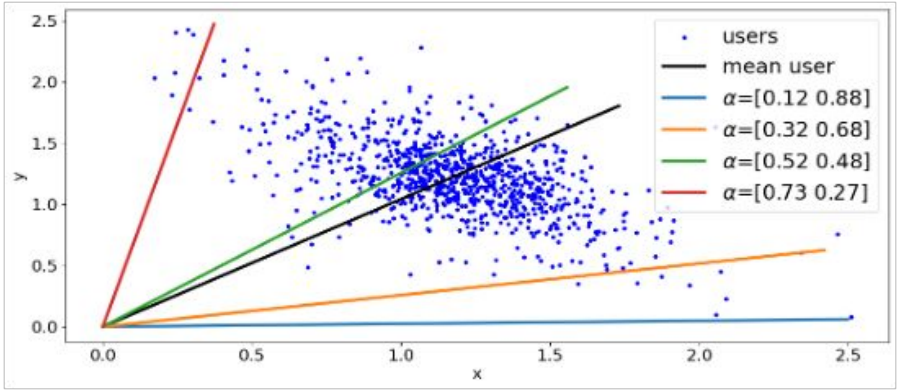
D = dim (# of factors) in matrix factorization

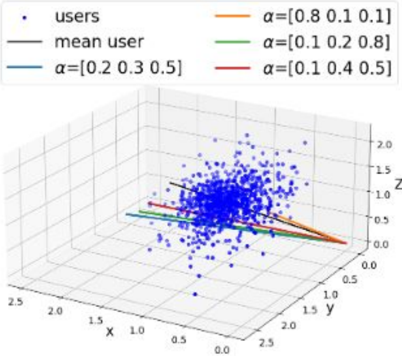
Dataset: MovieLens-100K

Platform can make specialization more likely by increasing the # of factors D.

Examples of equilibrium structure

No specialization regime





α = cost function weights parameter

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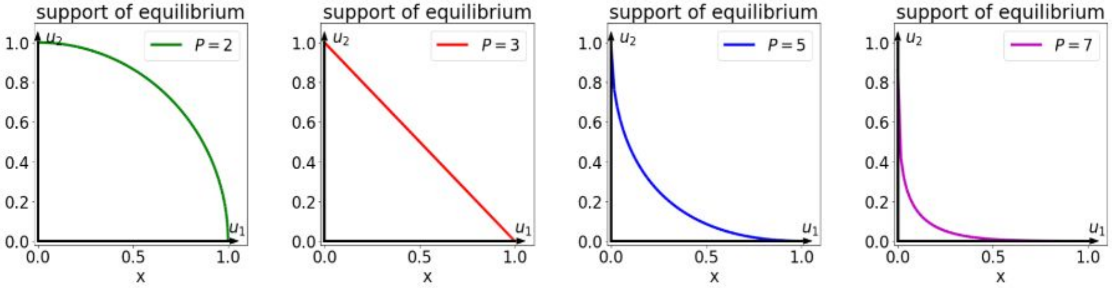
Specialization regime



User embeddings at standard basis vectors

Discussion

Although consumer-side effects of recommendations have received a lot of attention, producer incentives have been largely ignored.

We presented a high-dimensional model for producer competition in personalized recommender systems and investigated the potential for specialization by producers.

Our model opens the door to future investigation of content producer incentives in recommender systems.