

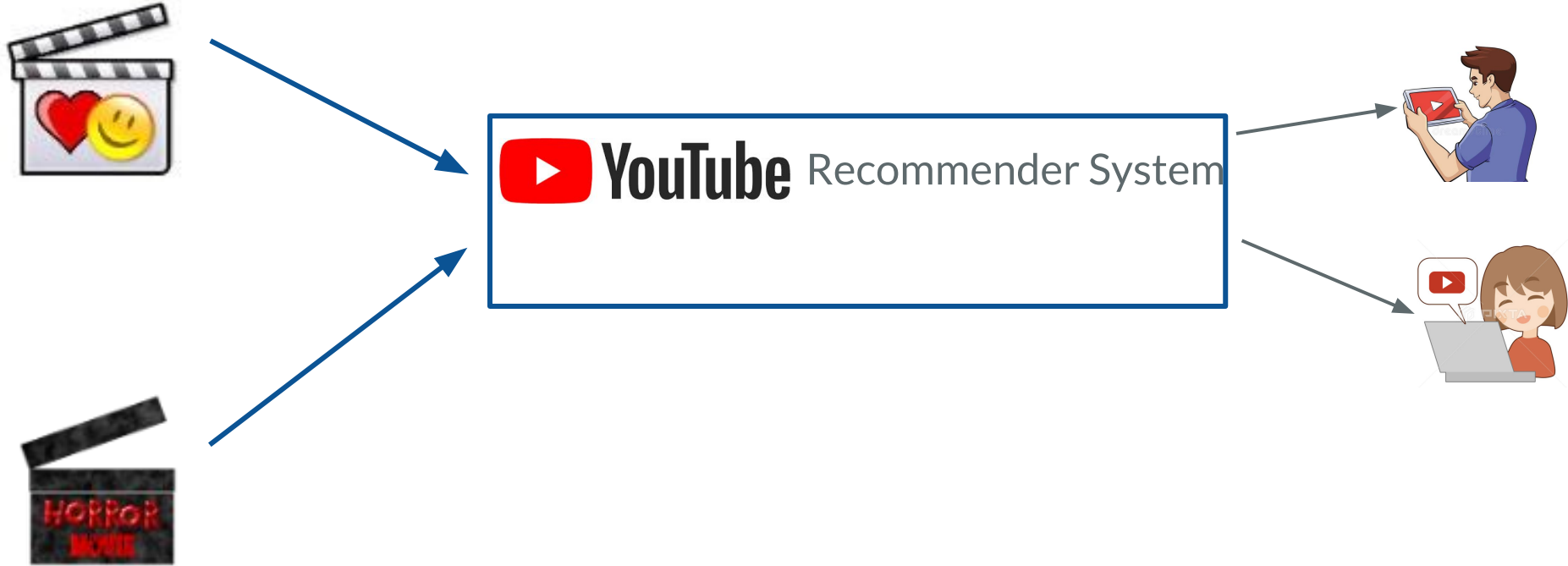
Supply-Side Equilibria in Recommender Systems

Meena Jagadeesan (UC Berkeley)

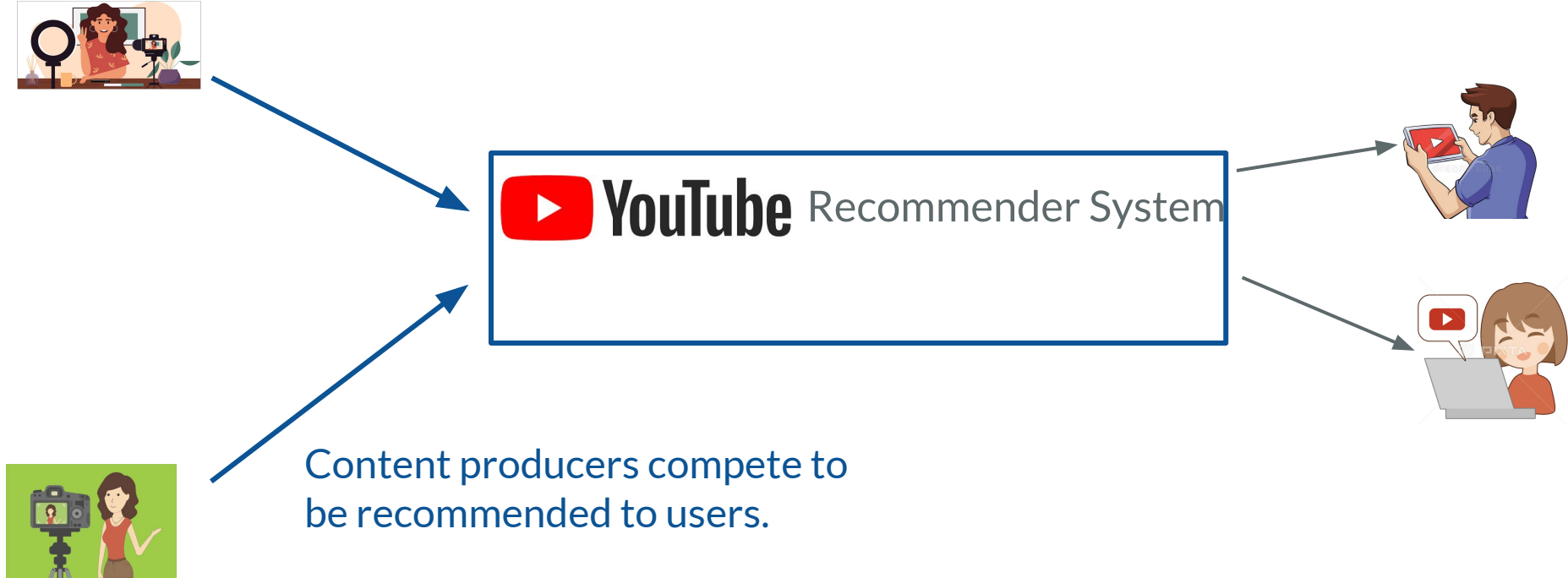
Joint work with Nikhil Garg (Cornell Tech) and Jacob Steinhardt (UC Berkeley)



Content recommendation as an isolated system



Reality: Content recommendation in a marketplace



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Strategically create
content that optimizes
for recommendations



Content producers compete to
be recommended to users.



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YouTube

Recommender System

Selects personalized recommendations



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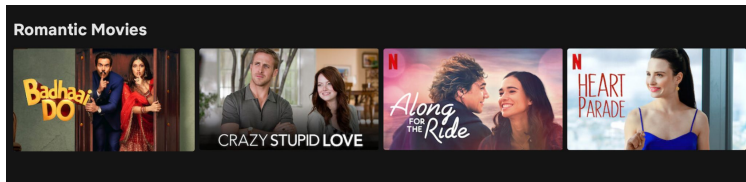
YouTube Recommender System

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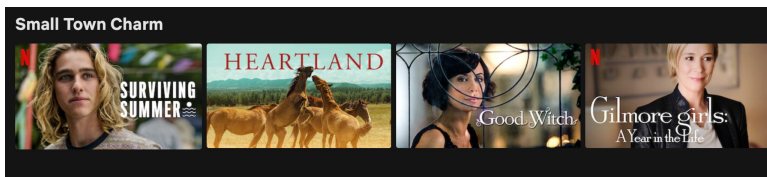
This paper: impact of recommender system on content created at equilibrium

How personalized recommendations impact producers



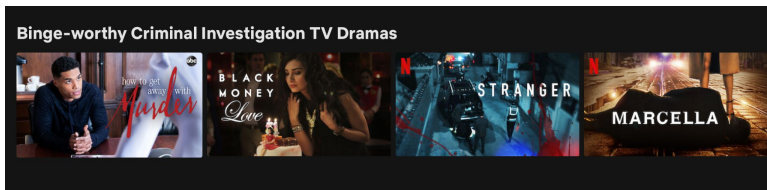
Niche content can reach the right audience!

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

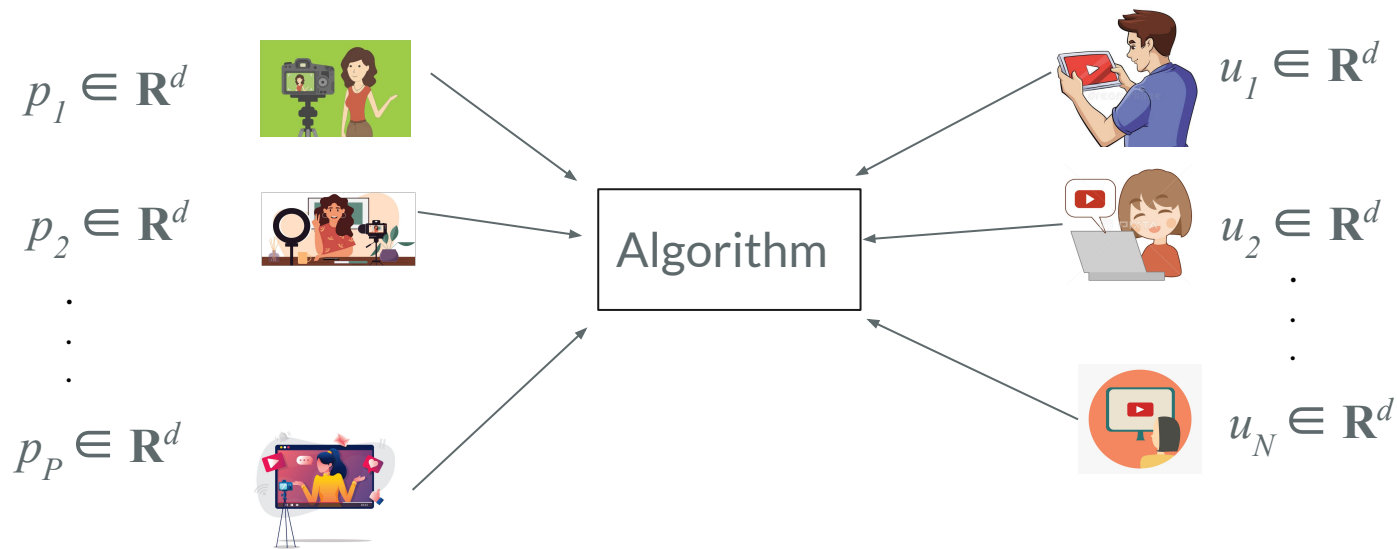
When do personalized recommendations lead to specialization?

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.

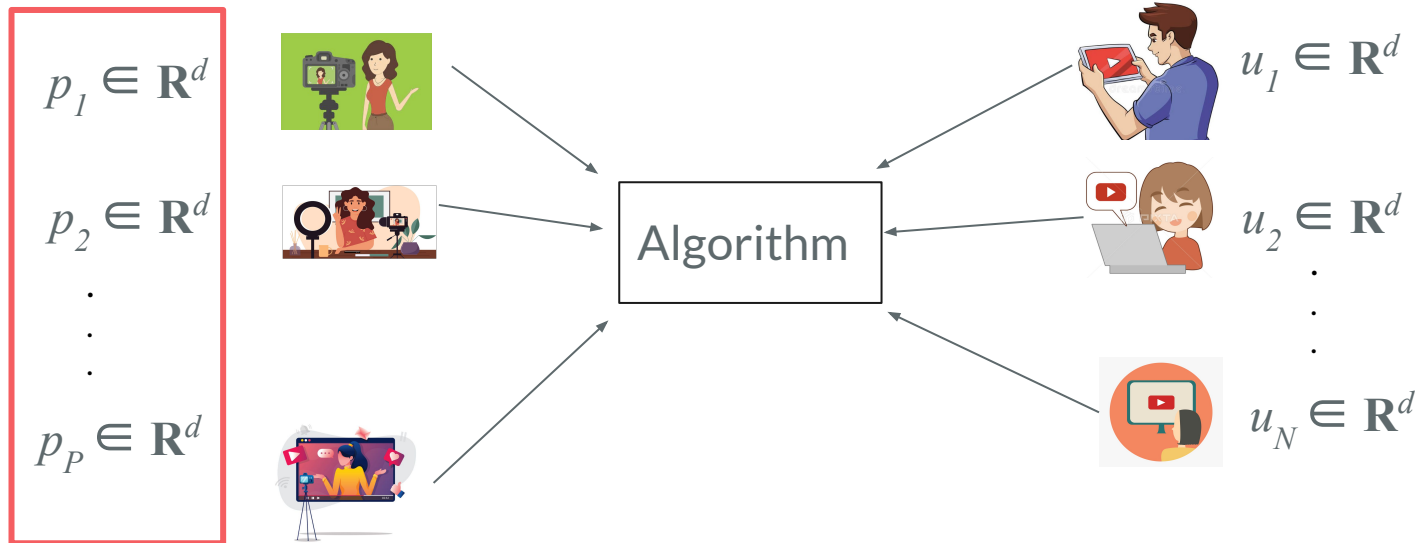
Overview of our model

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



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

Overview of our model

Producer profit:

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

Exposure (# of users won)

Fixed cost of
producing content

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

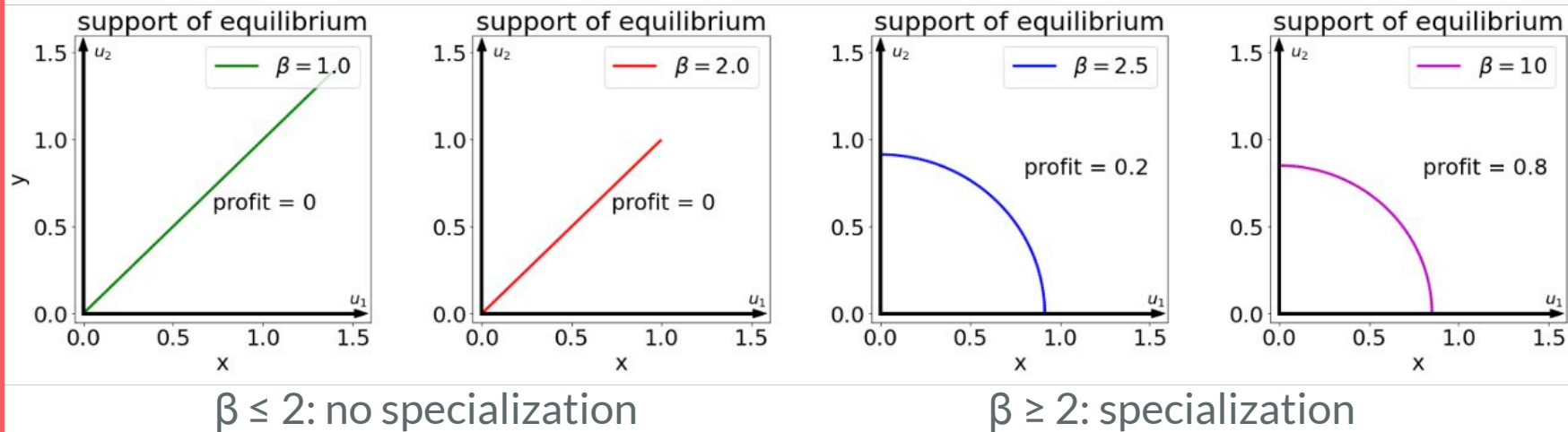
Characterization of when specialization occurs

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

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



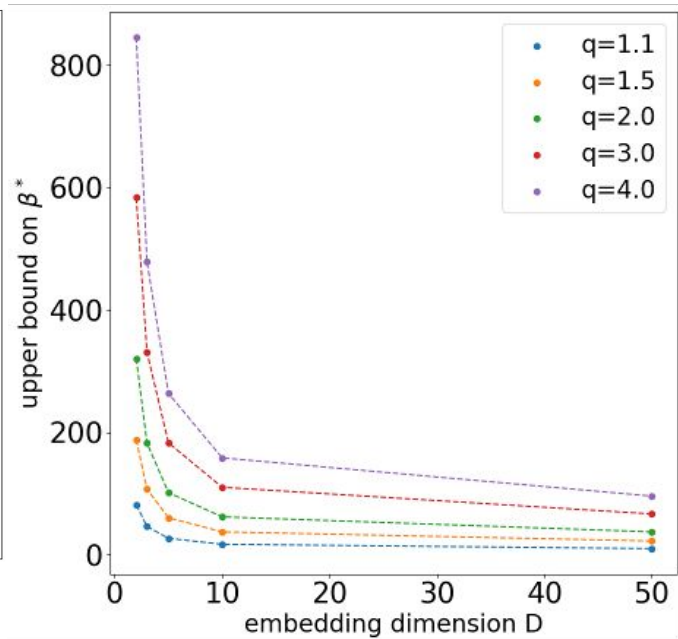
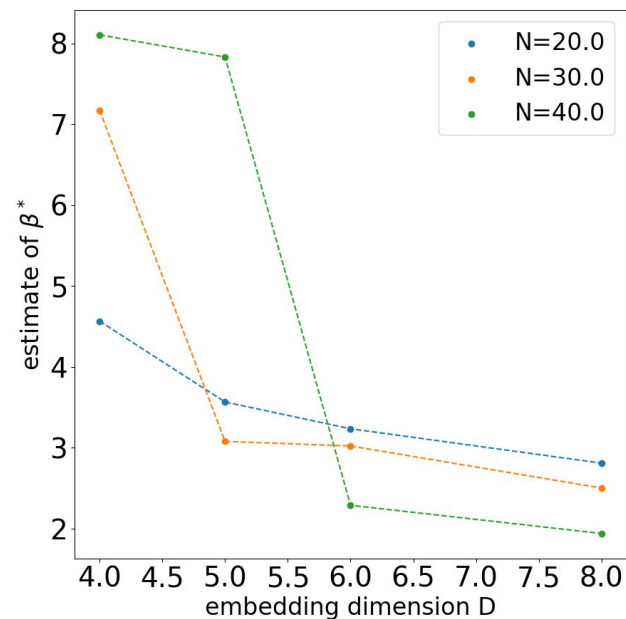
Whether specialization occurs depends on producer costs + user embeddings.

Impact of platform's algorithm

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

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q = cost function norm

N = # of users

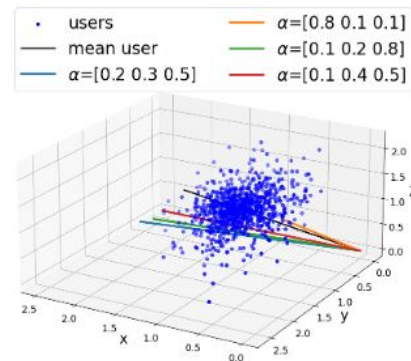
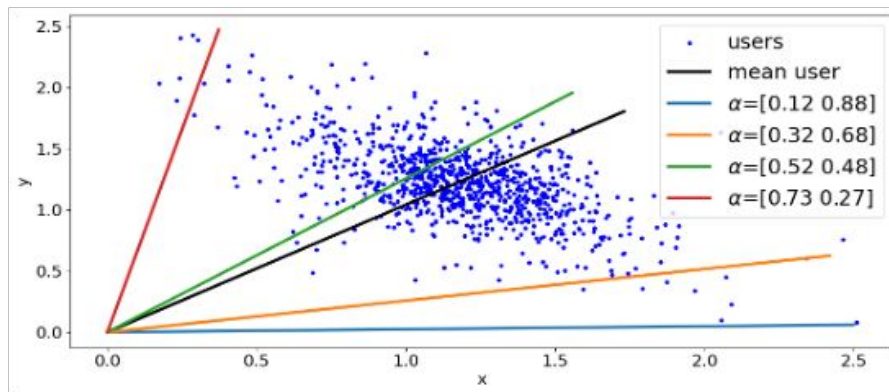
D = dim (# of factors) in matrix factorization

Dataset: MovieLens-100K

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

Examples of equilibrium structure

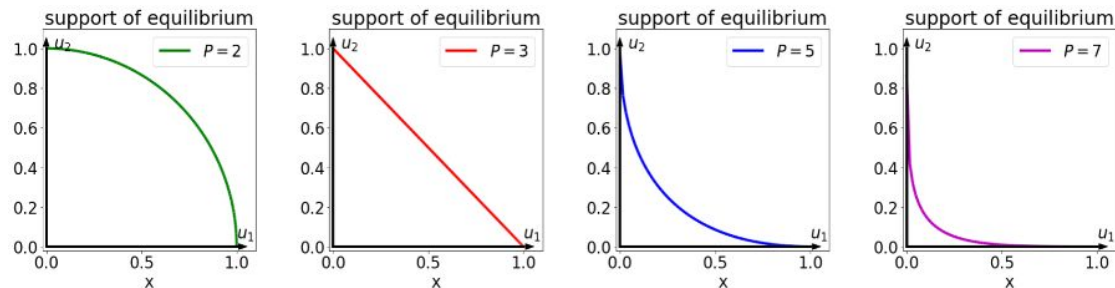
No specialization regime



α = cost function weights parameter

Dataset: MovieLens-100K

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.