Supply-Side Equilibria in Recommender Systems

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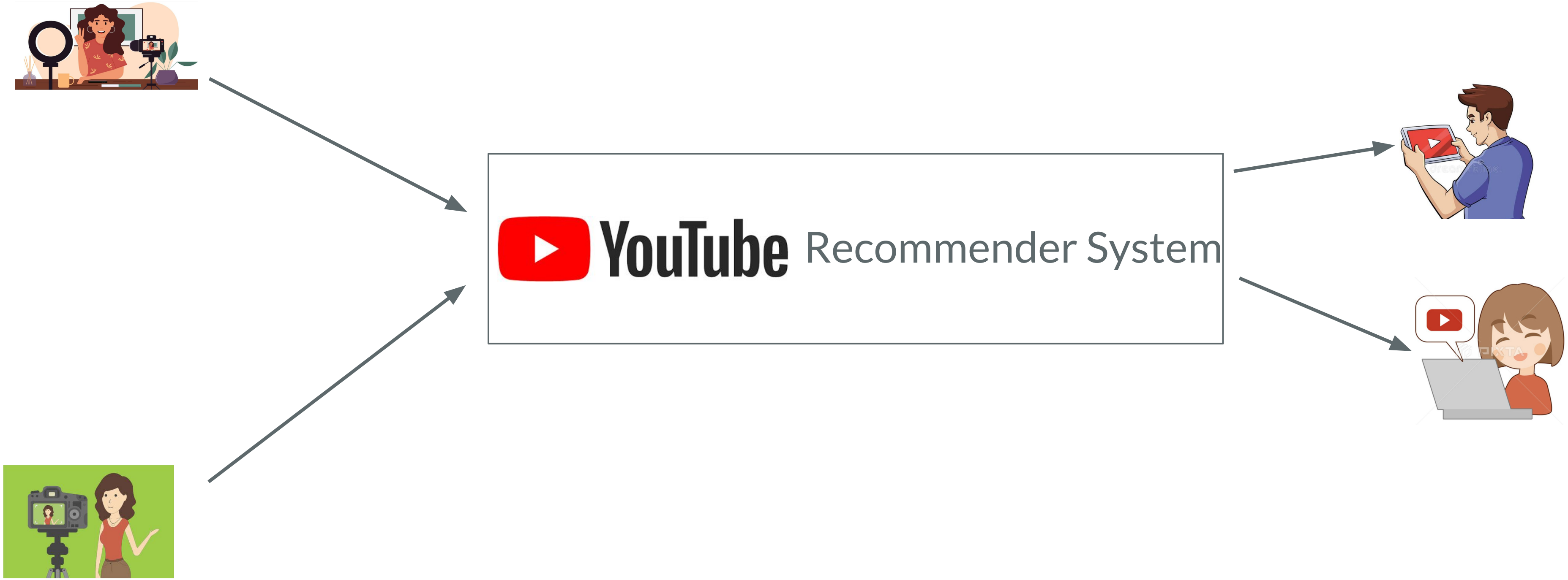
Joint work with Nikhil Garg (Cornell Tech) and Jacob Steinhardt (UC Berkeley)

Classical view: Analyze ML as an Isolated System

YouTube Recommender System

Content recommendation in a marketplace



Content recommendation in a marketplace

YouTube Recommender System

Content producers compete to
be recommended to users.

Content recommendation in a marketplace

Strategically create content that optimizes for recommendations

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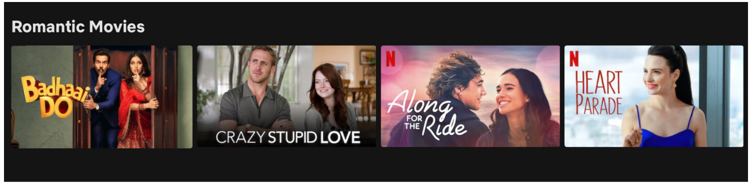
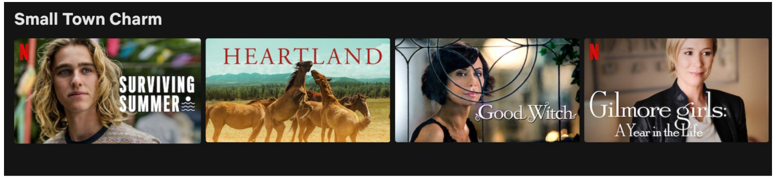
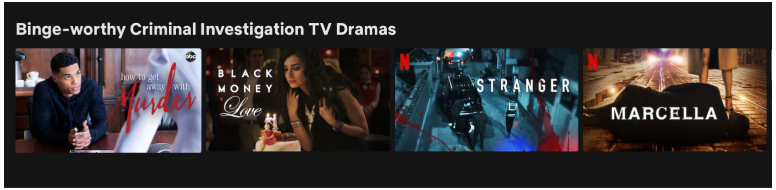
Offers **personalized recommendations**

Content producers compete to be recommended to users.

How personalized recommendations impact producers







Niche content can reach the right audience!

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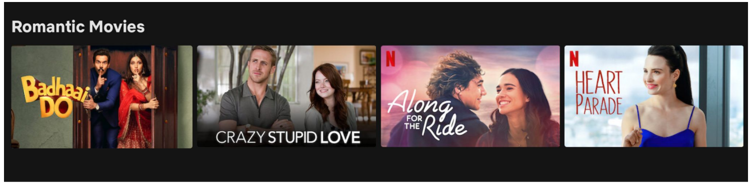

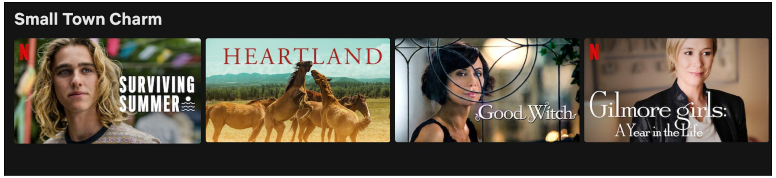

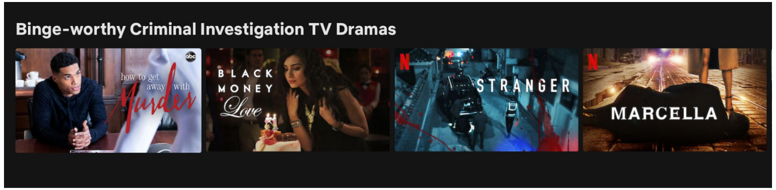

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But some niche content may only appeal to a small set of users.

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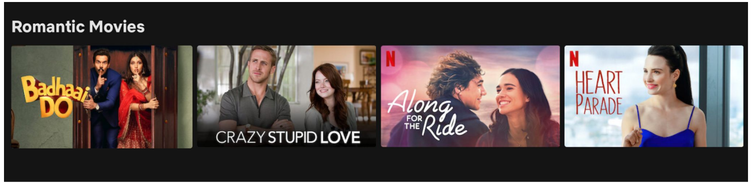
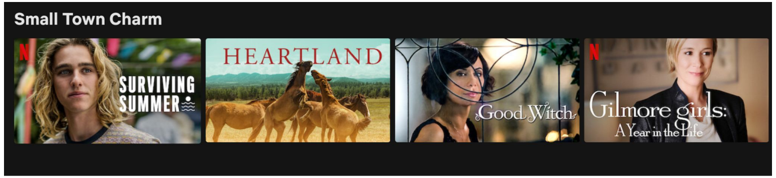
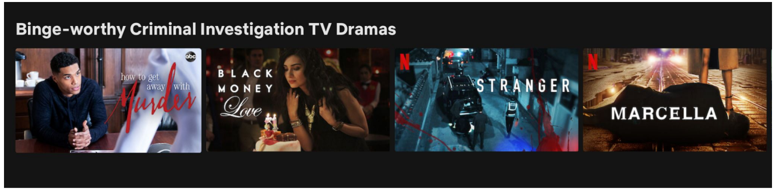






Niche content can reach the right audience!

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

Producers may be incentivized to either:

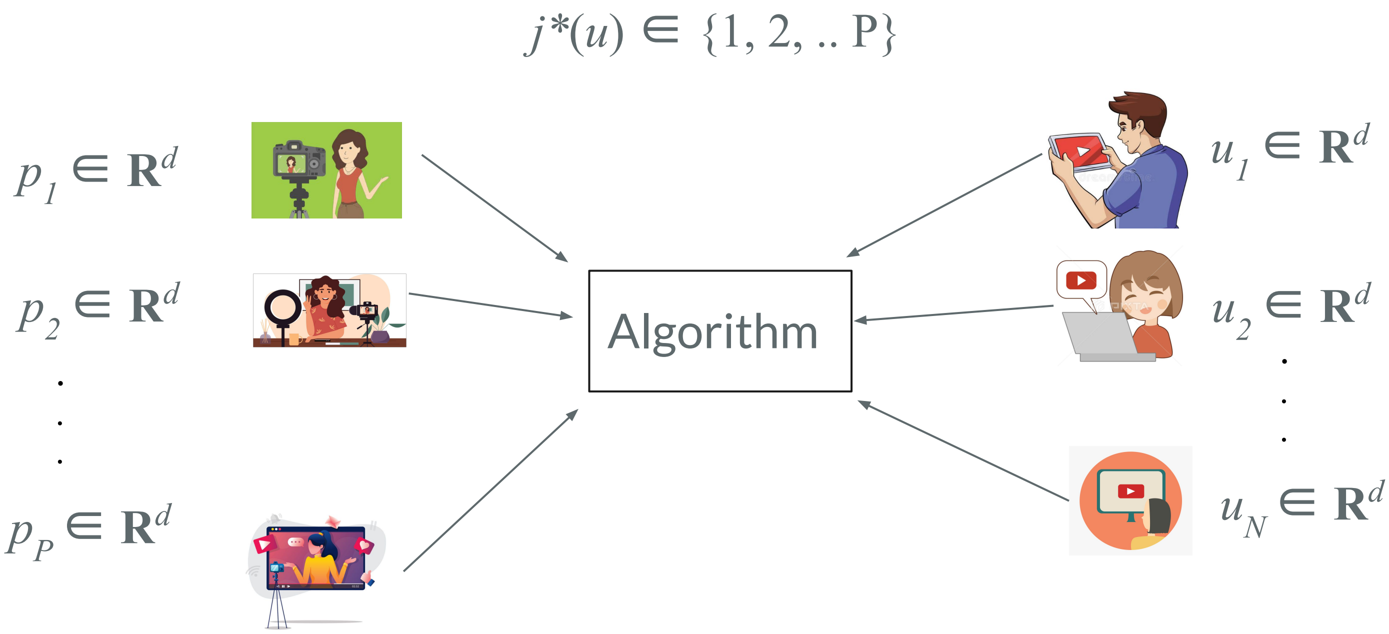
1. Create specialized content catered to a subpopulation.
2. Create mainstream content catered to the “average” user.

This paper

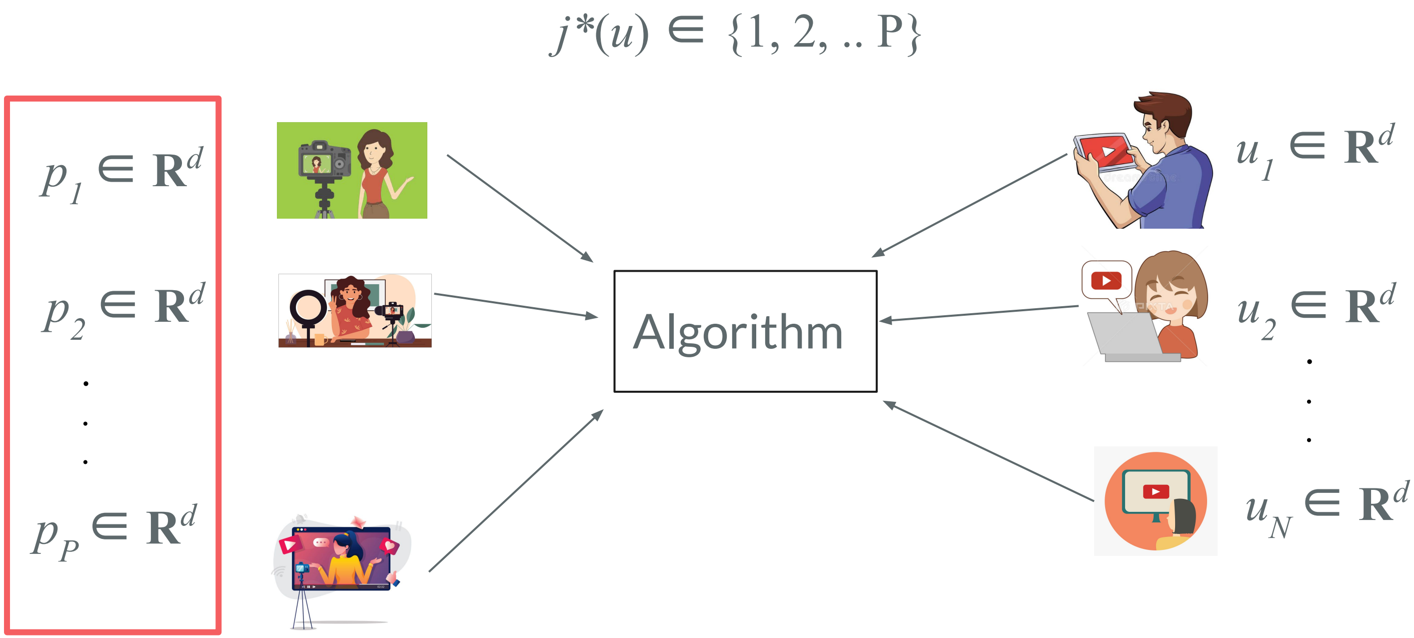
When do personalized recommendations lead to specialization?

What form does specialization take, and how does it impact market competitiveness?

Our model


$j^*(u) \in \{1, 2, .. P\}$
$p_1 \in \mathbf{R}^d$
$p_2 \in \mathbf{R}^d$
$p_P \in \mathbf{R}^d$
Algorithm
$u_1 \in \mathbf{R}^d$
$u_2 \in \mathbf{R}^d$
$u_N \in \mathbf{R}^d$

Our model



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

Our model

Producer profit:

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

# of users won

Fixed cost of producing content

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

β captures difficulty of excelling in many dimensions

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Features of model: high-dimension action space & heterogeneous user values

Informal summary of results

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We define specialization to be when multiple directions ("genres") in the equilibrium distribution, i.e.:

$$|\mathrm{Genre}(\mu)| := \{\, p \,/\, \|p\| \ \ s.t.\ p \in \mathrm{supp}(\mu) \,\}$$

Specialization ⇔ $|\mathrm{Genre}(\mu)| > 1$

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Result 1: We give a tight characterization of when specialization occurs.

Result 2: We analyze the specific form of specialization in concrete instances.

Result 3: We show that specialization can reduce market competitiveness.

Example: 2 Populations of Users, $P = 2$ producers

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

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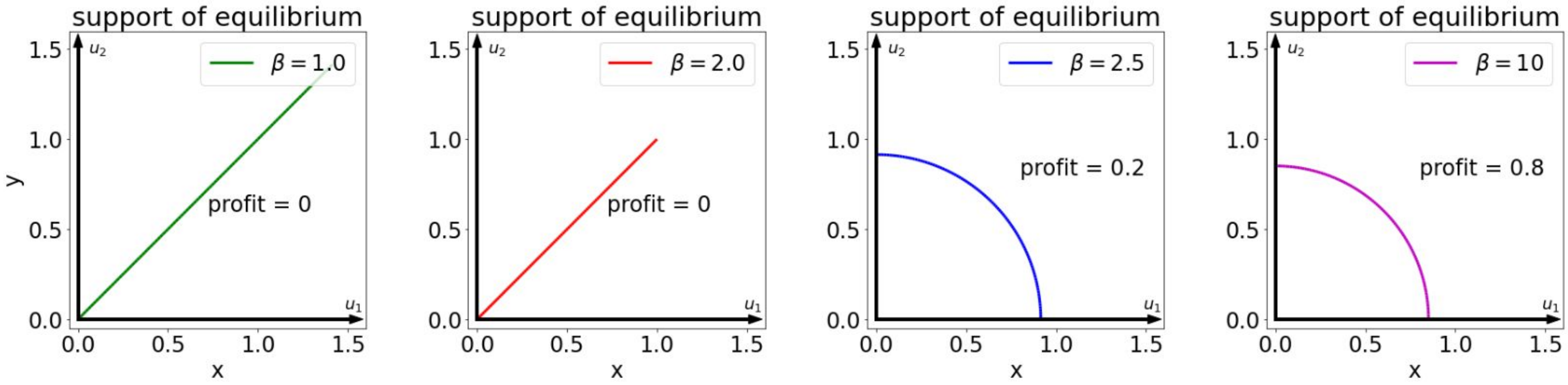

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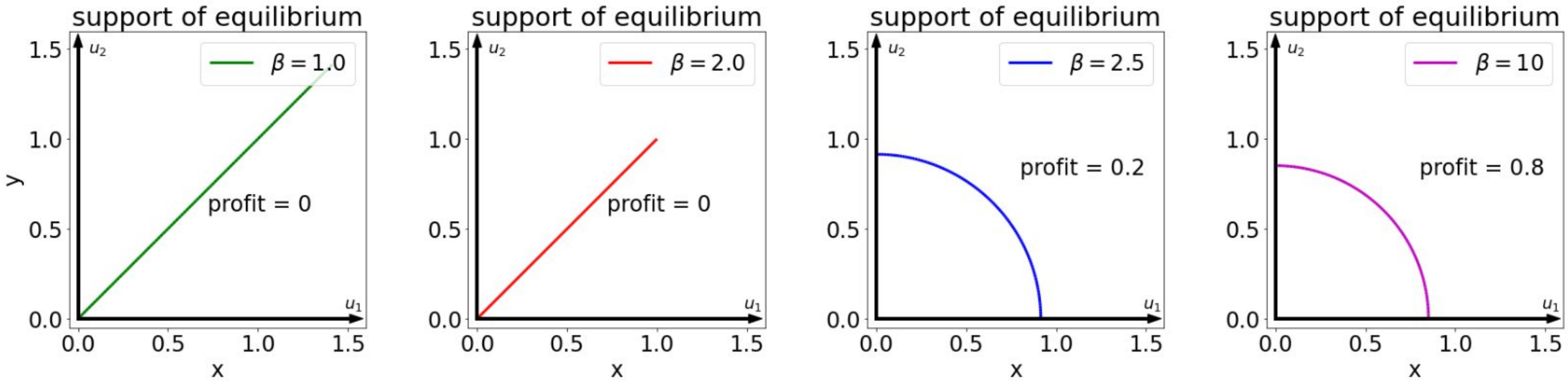

$\beta \leq 2$: single genre regime (**no specialization**) $\beta \geq 2$: multi-genre regime (**specialization**)

There is a **phase transition at $\beta = 2$** between $\mathrm{Genre}(\mu) = 1$ and $\mathrm{Genre}(\mu) = \infty$.

(Example of Result 1)

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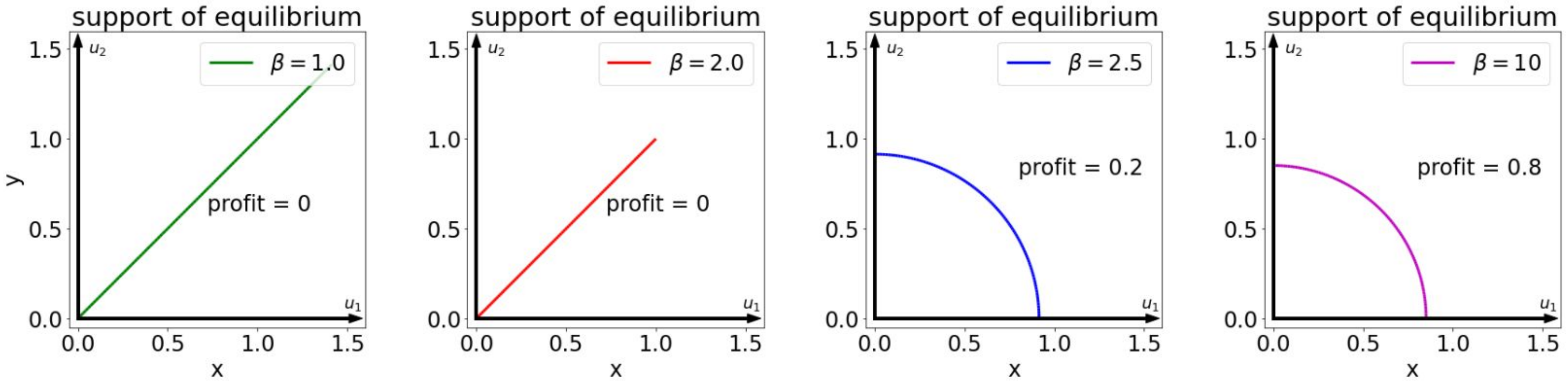

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(Example of Result 2)

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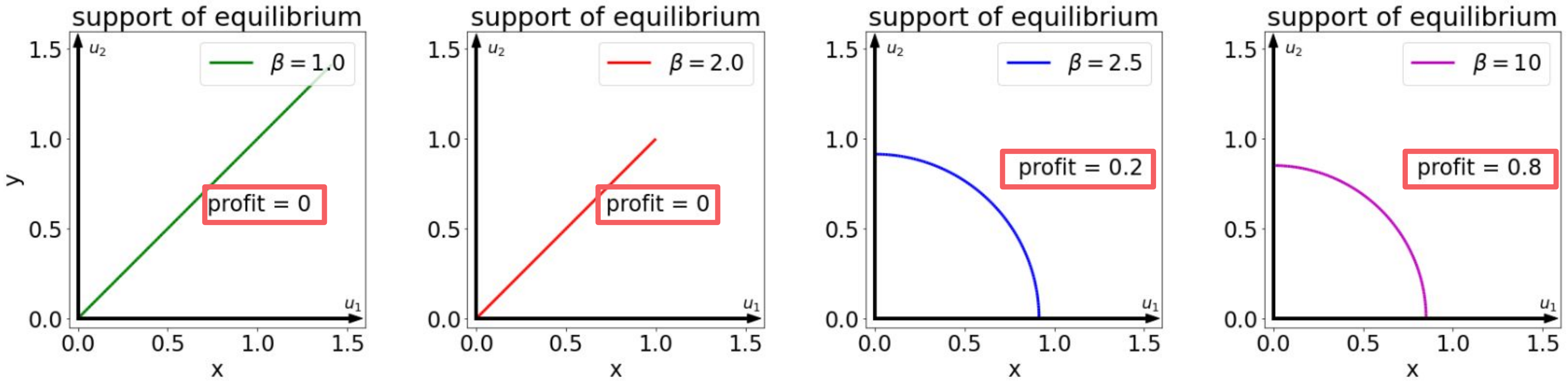

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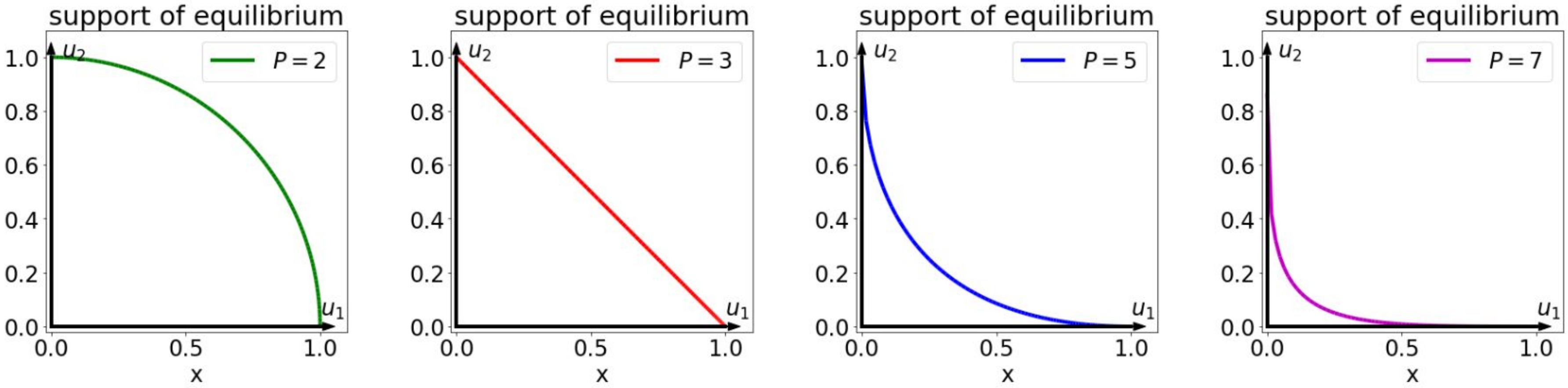
(Example of Result 3)

Another example: $P \geq 2$ producers

Consider $u_1 = [1, 0]$ and $u_2 = [0, 1]$ with $P \geq 2$ producers and cost function $c(p) = ||p||_2^2$.

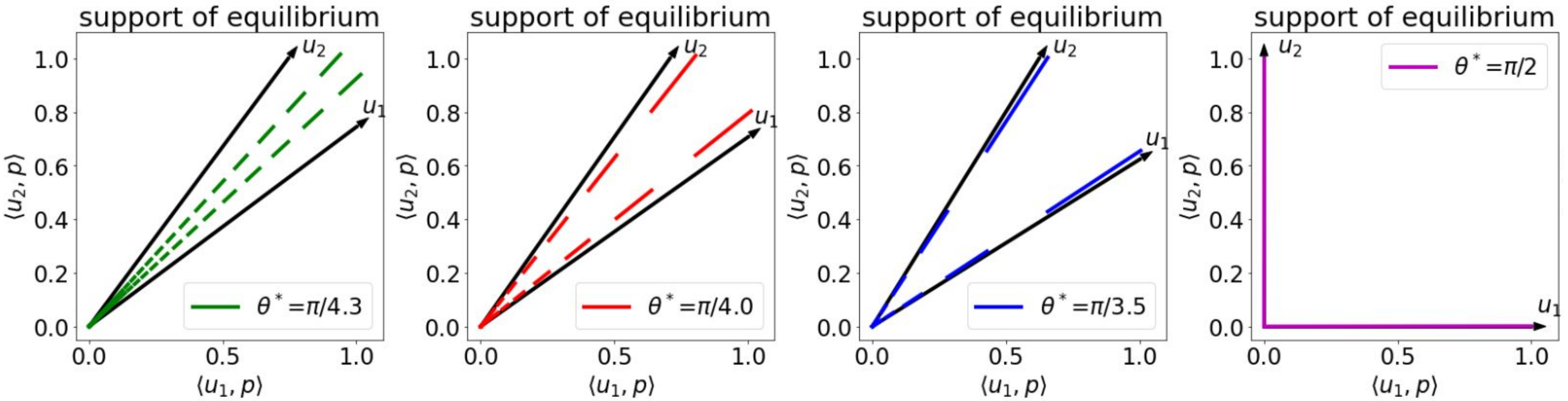


Specialization at infinite-genre equilibria takes different forms for different values of P.

(Another example of Result 2)

Another example: $P = \infty$ producers

Consider 2 users at u_1 and u_2 with $P = \infty$ producers and cost function $c(p) = ||p||_2^\beta$.



Finite-genre re-emerge in the infinite-producer limit (but not exactly aligned with user vectors) .

(Another example of Result 2)

Technical ingredients

We develop technical methods to analyze high-dimensional competition, including:

- We relate the existence of a single-genre equilibrium to strong duality of an optimization program that we construct.
- We show a decoupling lemma that transforms the high-dimensional action space into 1-dimensional functional equations.
- Our formalization of specialization does not require reasoning about asymmetric equilibria.

Discussion

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

We presented a framework for supply-side competition in personalized rec systems and investigated the potential for specialization by producers.

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We presented a framework for supply-side competition in personalized rec systems and investigated the potential for specialization by producers.

Opens the door to future investigation of supply-side behavior in recommender systems:

- Analyze how platform learning dynamics impact production over time (Hu*, J.*, Jordan, Steinhardt)
- How is the welfare of users impacted by personalization and supply-side effects?
- How can the platform design a recommendation algorithm optimizes overall welfare?