

User Satisfaction and Creator Productivity Trade-Offs

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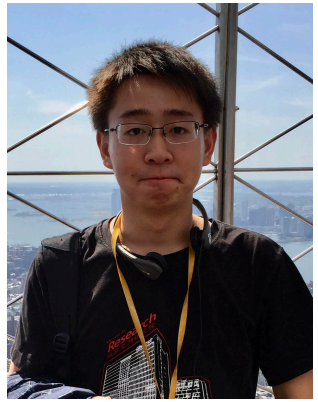
Acknowledgement



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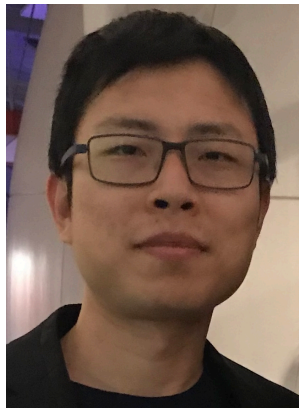

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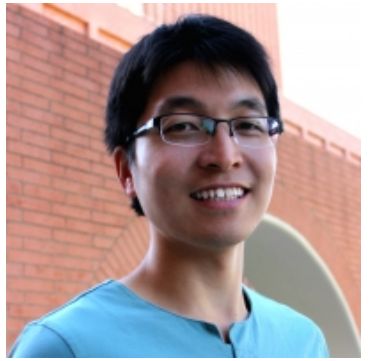

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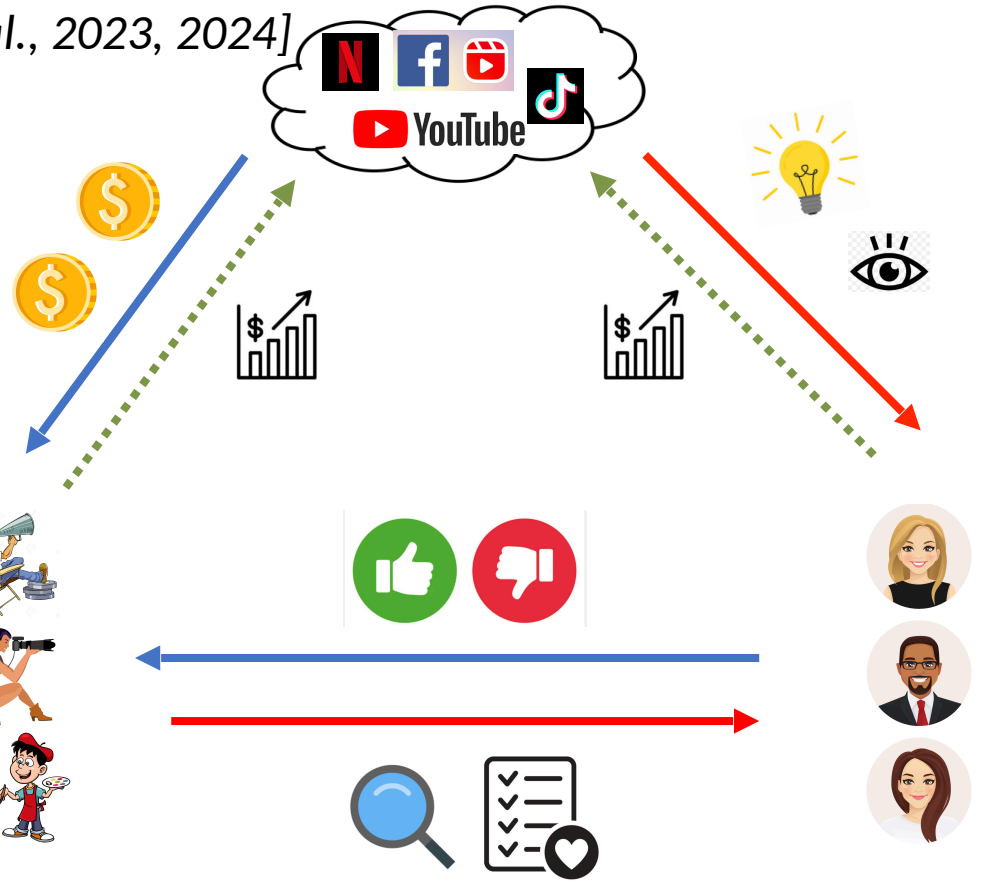
Game-theoretic modeling of content creation dynamics

- Information Retrieval games *[Ben-Porat et al., 2019, Madmon et al., 2024]*
- Exposure games *[Hron et al., 2023, Jagadeesan et al., 2023]*
- Content Creator Competition (C^3) games *[Yao et al., 2023, 2024]*

- Our framework:
  - Cournot C^3 (C^4) games
  - Extended from C^3
  - Echoes Cournot Competition *[Cournot, 1838]*

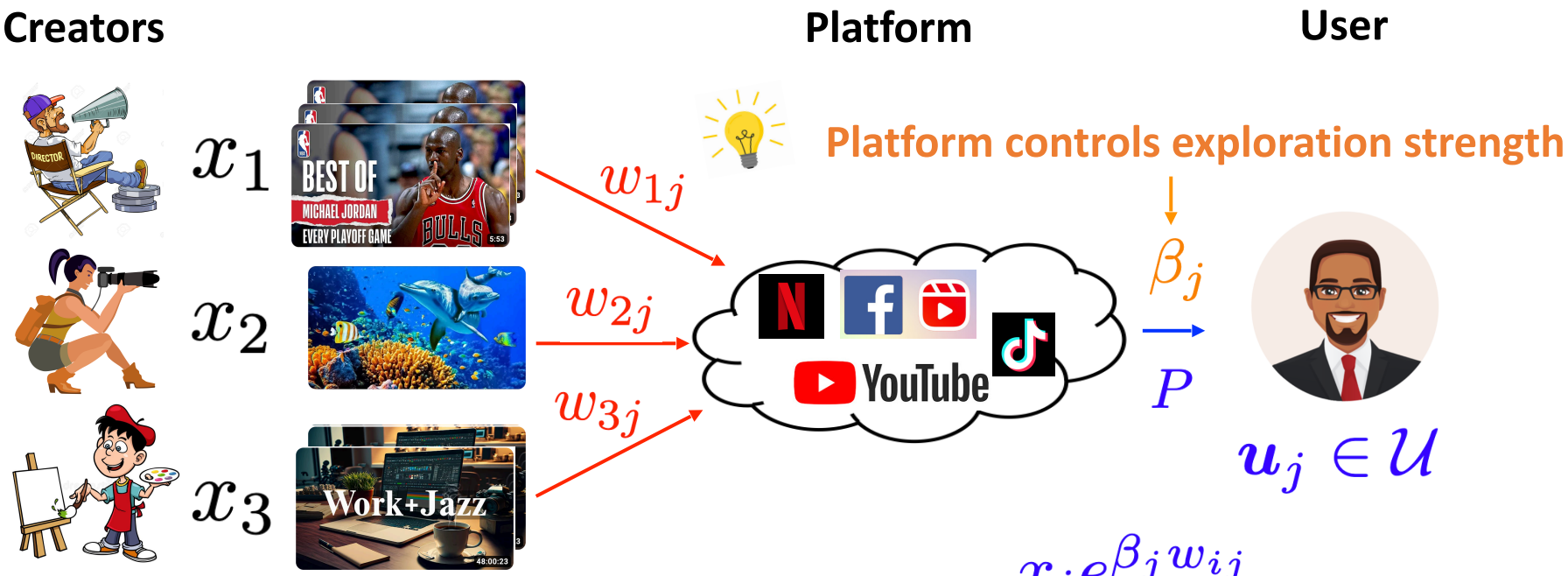


☑ I'm aware of and commit to my niche.
☑ what content I should produce?
☑ How much time/effort I should spend?

Cournot Competing Content Creation (C^4) Game

- Basic components: *n* creators, a population of users $\mathcal{U} = \{\boldsymbol{u}_j \in \mathbb{R}^d\}_{j=1}^m$ and a platform with a relevance measurement $w_{ij} \in [0, 1]$

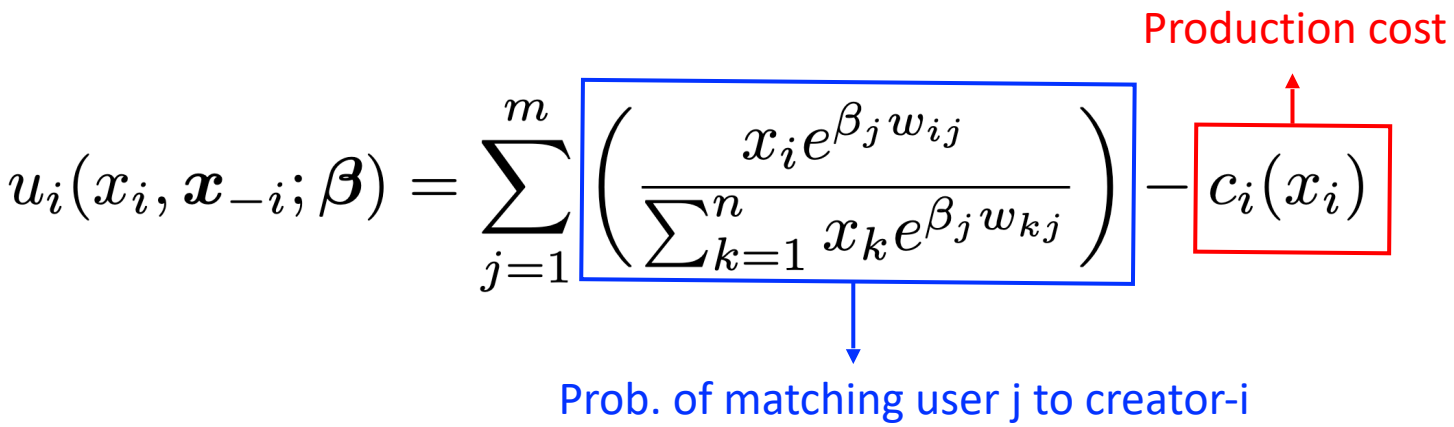
- Each creator chooses production quantity x_i
- Platform allocate traffic to each piece of content based on soft-max rule from relevance measures, using personalized exploration strengths
- Creators' payoffs: the receive traffic minus the production cost



$$P(i \to j) = \frac{x_i e^{\beta_j w_{ij}}}{\sum_{k=1}^{n} x_k e^{\beta_j w_{kj}}}.$$

Creators' payoff functions

- Expected payoff = traffic - cost:



- The platform controls the personalized exploration strength $\boldsymbol{\beta} = (\beta_1, \cdots, \beta_m)$
- Each creator optimizes her payoff with gradient-based dynamics

Stability of *C*^{4}

Theorem 1 [Informal] Pure Nash equilibrium (PNE) exists in any *C*^{4} with convex costs, and gradient ascent dynamics converge to the unique PNE.

- When costs are convex, creator-i's payoff function is concave in creator-i's strategy and convex in other creators' strategies
- With these properties, we can verify *C*^{4} is a strict monotone game *[Rosen, 1965]* and thus has a unique PNE $\boldsymbol{x}^* = (x_1^*, \cdots, x_n^*)$
- This allows us to further investigate the properties of PNE $\boldsymbol{x}^*(\boldsymbol{\beta})$

User satisfaction and creator productivity

Definition. The user satisfaction metric under the exploration policy is $\boldsymbol{\beta} = (\beta_1, \cdots, \beta_m)$ is given by

$$U(\boldsymbol{x}^*(\boldsymbol{\beta}); \boldsymbol{\beta}) = \sum_{j=1}^{m} \sum_{i=1}^{n} \left(\frac{w_{ij} x_i^* e^{\beta_j w_{ij}}}{\sum_{k=1}^{n} x_k^* e^{\beta_j w_{kj}}} \right),$$

and the total content creation volume is given by

$$V(\boldsymbol{x}^*(\boldsymbol{\beta})) = \sum_{i=1}^{n} x_i^*.$$

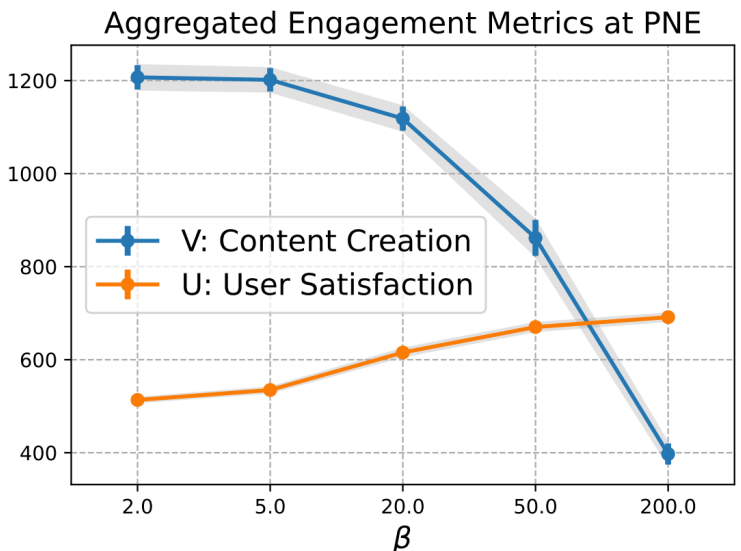
- The user satisfaction *U* is usually considered as a **short-term** evaluation metric, while the total content creation volume *V* concerns the **long-term** content supply

Theoretical result

Tradeoff between U and V

Theorem 2 When the user population is homogeneous, ***U* is increasing** in β and ***V* is decreasing** in β.

- Reveals an intrinsic tradeoff between user engagement and creator engagement in content recommendation platforms!
- Empirically, we can verify such observation holds for general user population as well.



Theoretical result

Optimize a hybrid social welfare

- In practice, the platform usually needs to balance the short-term and long-term goal
- This can be achieved by optimizing a linear combination of *U* and *V*

$$W_\lambda(\boldsymbol{x}^*(\boldsymbol{\beta}); \boldsymbol{\beta}) = U(\boldsymbol{x}^*(\boldsymbol{\beta}); \boldsymbol{\beta}) + \lambda V(\boldsymbol{x}^*(\boldsymbol{\beta}); \boldsymbol{\beta}).$$

- To optimize *W*, the platform needs to solve

$$\begin{aligned} \text{Find} \quad & \arg\max_{\boldsymbol{\beta} \in \mathbb{R}^m_{\geq 0}} W_\lambda(\boldsymbol{x}^*(\boldsymbol{\beta}), \boldsymbol{\beta}) \\ s.t. \quad & \boldsymbol{x}^*(\boldsymbol{\beta}) \text{ is the PNE of } \mathcal{G}. \end{aligned}$$

- We can derive the gradient of *W* w.r.t. $\boldsymbol{\beta}$ using chain rules and implicit function theorem!

☑**Please check out our paper for more details!**