Research Track | Economics, Online Markets, and Human Computation

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Clickbait vs. Quality: How Engagement-Based Optimization Shapes the Content Landscape in Online Platforms

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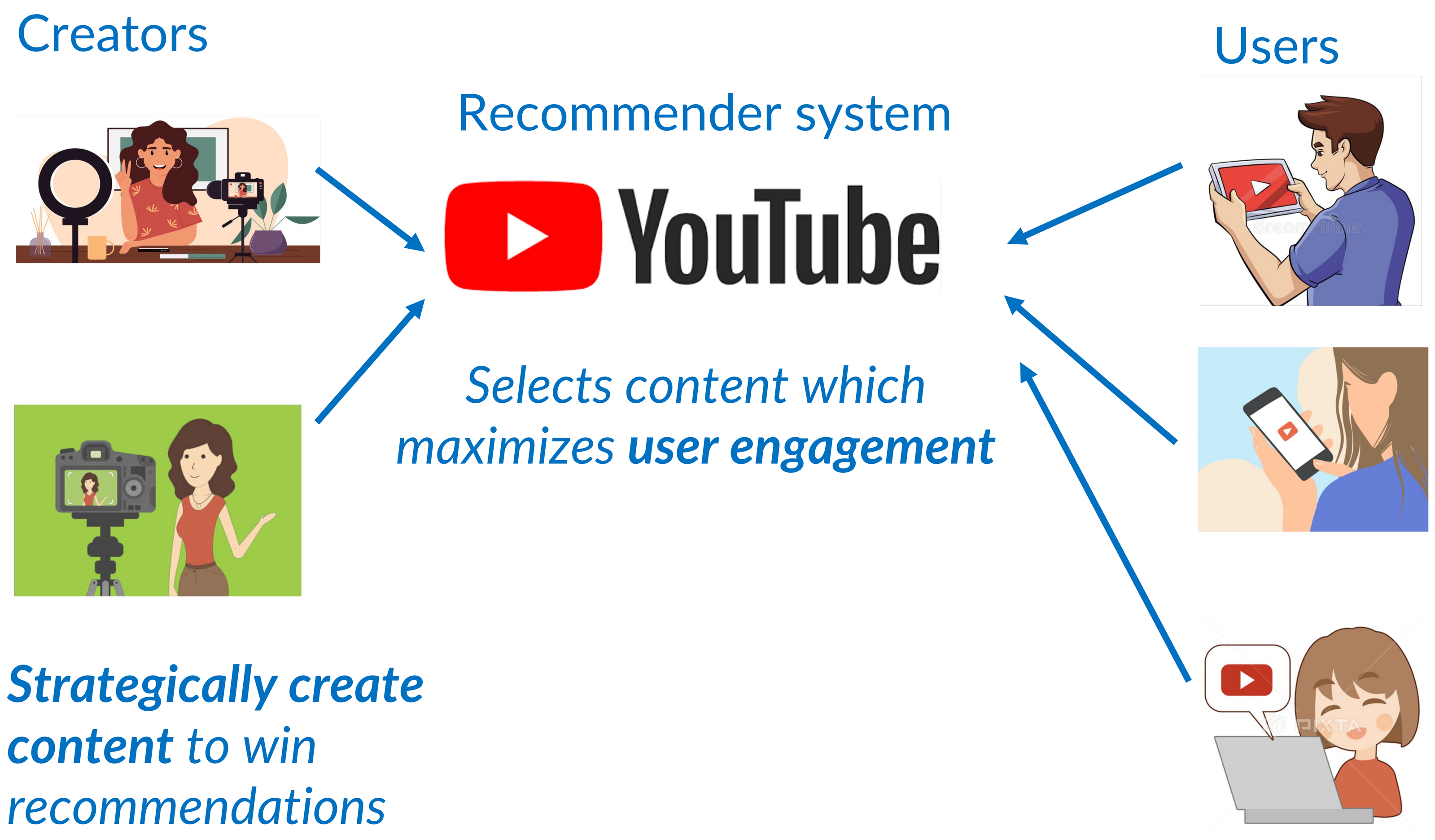
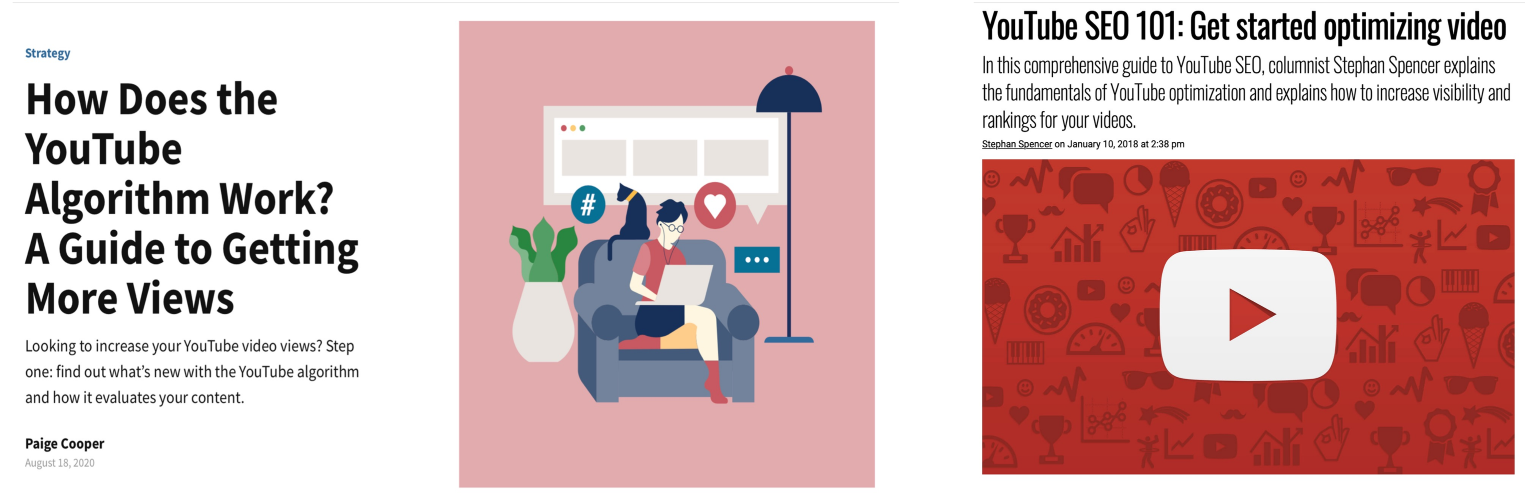
Content creator incentives

In a recommender system, the content landscape is shaped by the **strategic choices of content creators**.



Content creators often **game** the engagement metric (e.g., by using clickbait, offensive language, addiction, etc.).



Main question: How does **gaming** affect the content landscape and the platform's downstream performance?

Model: Game between Creators

Each creator chooses $p = [p_{costly}, p_{cheap}] \in \mathbf{R}^2_{\geq 0}$.

quality | gaming

Rec sys maximizes an **engagement metric** M:

$$j^*(t; [p_1, \ldots, p_P]) = argmax_{j \in [P]} (M(p_j) \cdot 1[f(p_j, t) \geq 0])$$

User tolerance for gaming | Engagement if user consumes the content | User consumes recommendation only if utility is nonnegative.

Creator payoff depends on **rec sys policy** and **costs**:

$$\mathbf{P}(p_j \mid p_{-j}, T) = \mathrm{E}_{t \sim T}\left[j = j^*(t; [p_1, \ldots, p_P]) \text{ and } 1[f(p_j, t) \geq 0]\right] - c(p)$$

Creator wins recommendation | User consumes content | Creator costs

Impact of **quality vs. gaming**:

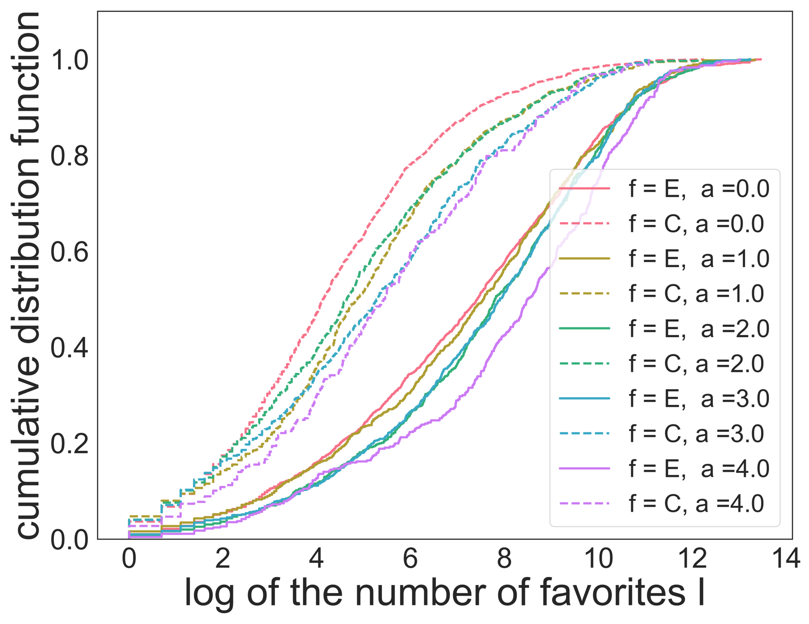
$p_{costly} \uparrow$ => Engagement M ↑, User utility f ↑, Creator costs c ↑ (expensive)

$p_{cheap} \uparrow$ => Engagement M ↑, **User utility f ↓**, Creator costs c ↑ (cheap)

Our focus: the **symmetric mixed Nash equilibria** in between creators (**determines content landscape**).

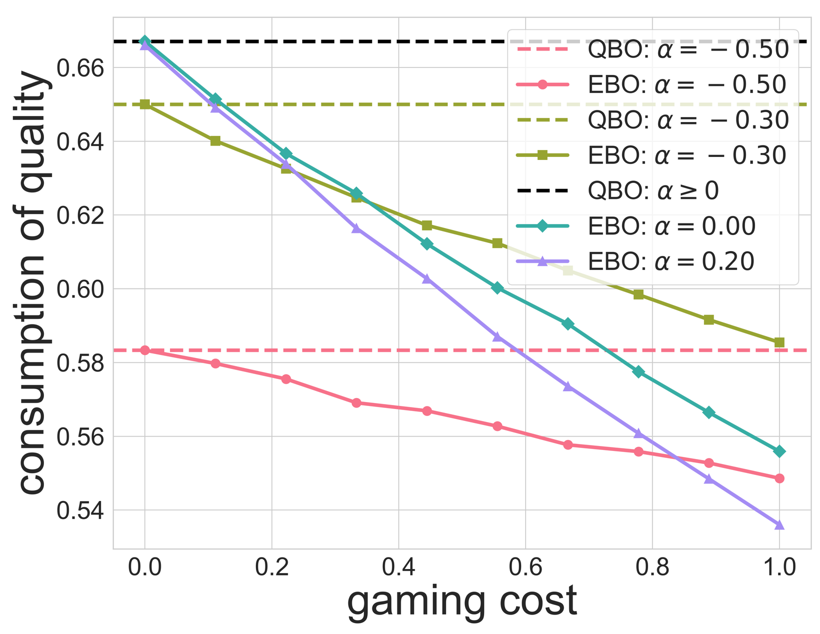
Our main results

High-level finding: Content creator incentives to **game** an engagement metric disrupt the **content landscape** and influence downstream **engagement**, **welfare**, and **quality**.

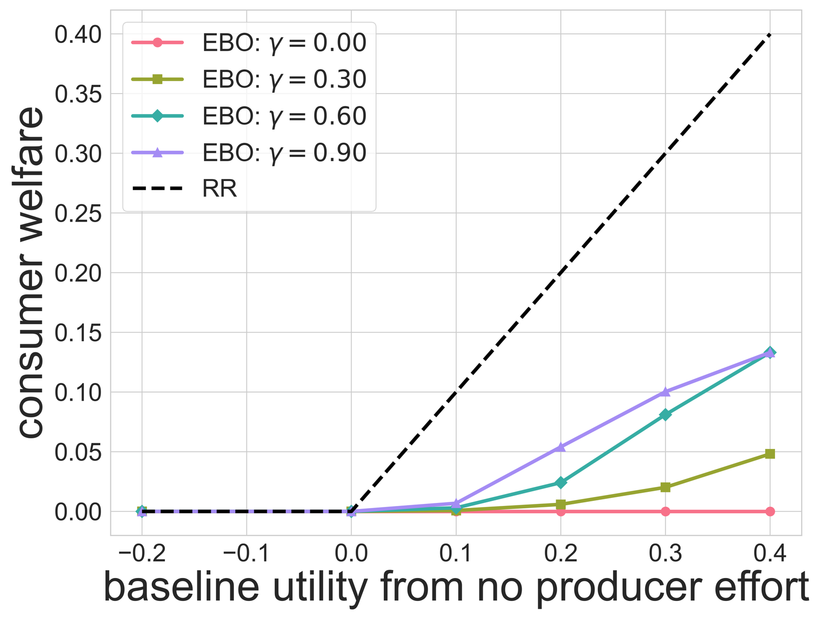


Twitter dataset (Milli et al., 2023)

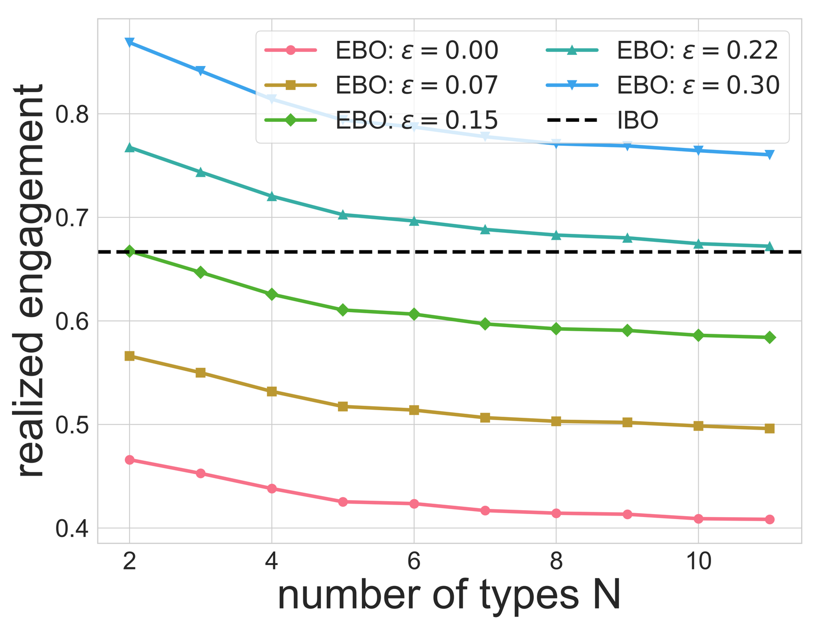
Finding 1: Gaming tricks and quality investment are **positively correlated** in the content landscape.



Finding 2: Making the engagement metric costlier to game can **reduce content quality**.



Finding 3: Optimizing engagement can lead to **lower user welfare** than random recommendations.



Finding 4: Optimizing engagement can lead to **lower user engagement** than optimizing quality.

Methodology

We propose a **stylized model** for the game between creators who compete for recommendations.

We solve for the **equilibria in the game between creators** (which determines the **content landscape**).

When evaluating a recommendation policy, we factor in the **endogeneity of the content landscape**.

References

[1] Ben-Porat, Tennenholtz. "A game-theoretic approach to recommendation systems with strategic content providers." NeurIPS 2018.
[2] Kleinberg, Raghavan. "How do classifiers induce agents to invest effort strategically?". EC 2019.
[3] Jagadeesan, Garg, Steinhardt. "Supply-Side Equilibria in Recommender Systems". NeurIPS 2023.