

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

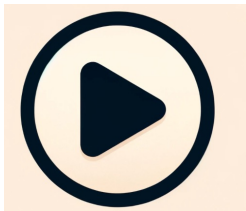
**Meena Jagadeesan (UC Berkeley)**

Joint work with Nicole Immorlica and Brendan Lucier (Microsoft Research)

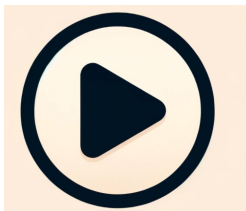


# Classical View: Recommender System in Isolation

Content



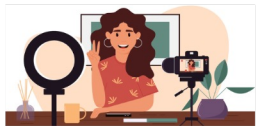
Content



*Recommend video that maximizes an **engagement metric***

# Reality: Content Recommendation Marketplace

Content creator



Content creator

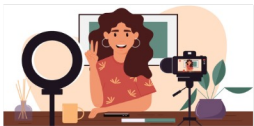


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Creators strategically design content to win recommendations.

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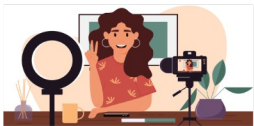


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Content creators can **game** the engagement metric, which affects the **supply-side landscape of content**.

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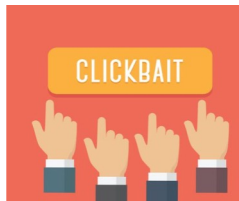


*Content creator*



**Continuing our work to  
improve recommendations on  
YouTube**

By The YouTube Team  
Jan. 25, 2019



You might remember that a few years ago, viewers were getting frustrated with clickbaity videos with misleading titles and descriptions ("You won't believe what happens next!"). We responded by updating our system to

*an engagement metric*

*mendations.*

Content creators can **game** the engagement metric, which affects the supply-side landscape of content.

# Main question

How do **gaming tricks** affect the supply-side landscape and the downstream performance of the recommender system?

# Overview of our game-theoretic model

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- Content creators compete for recommendations.
- The recommendation policy (optimizing engagement) influences creator payoffs.
- Content creators can employ **gaming tricks** as well as **quality investment**.

We solve for the **equilibria of this game**, which determines the **supply-side landscape**.

# Summary of our findings

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

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

Finding 4: Optimizing engagement can be **suboptimal for engagement**.



# Conclusion

In recommender systems, the supply-side landscape of content is shaped by content creators who strategically respond to the recommendation policy.

**Our focus:** engagement-based recommendations which reward gaming tricks (e.g., clickbait) and quality investment

**High-level finding:** Content creator incentives disrupt the supply-side landscape and thus downstream quality and user welfare.

**Broader takeaway:** Need to factor in endogeneity of the content landscape when evaluating a recommender system