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

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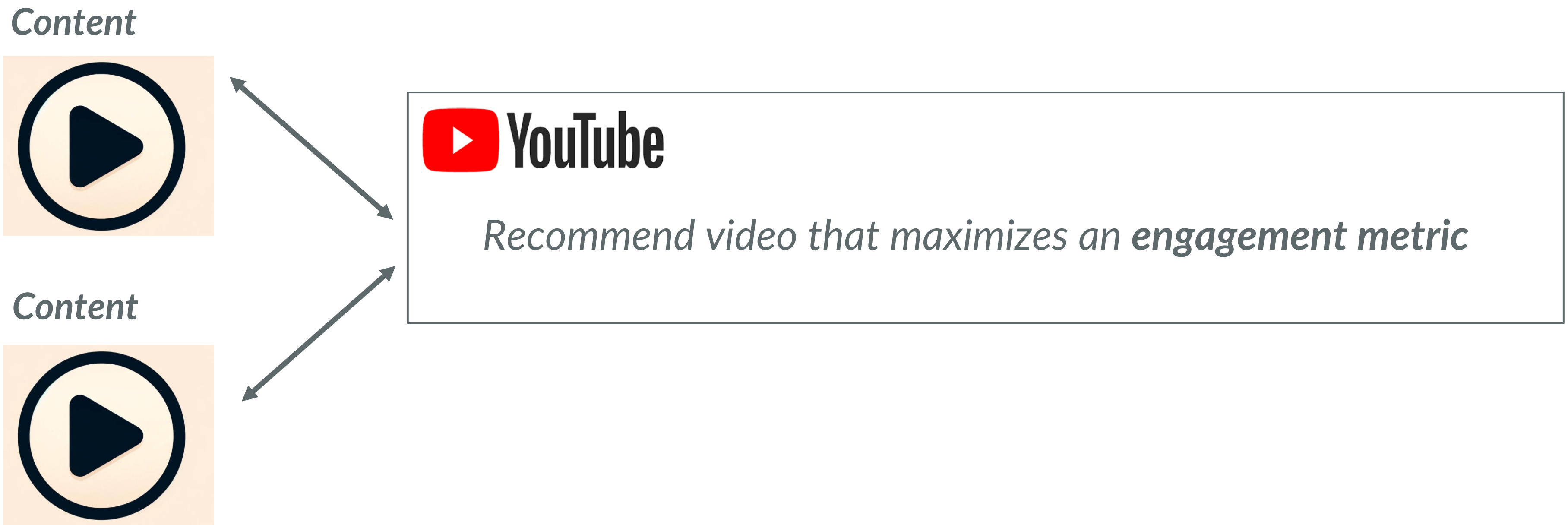
Classical View: Recommender System in Isolation



Reality: Content Recommendation Marketplace

Content creator

YouTube

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

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Creators strategically design content to win recommendations.

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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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- The recommendation policy (optimizing engagement) influences creator payoffs.
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We solve for the **equilibria of this game**, which determines the **supply-side landscape**.

Summary of our findings

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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.

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 influence downstream content quality and user welfare.

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