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

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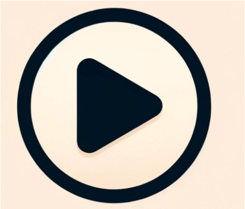
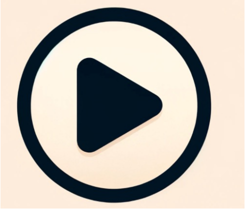
Classical View: Recommender System in Isolation

Content



Content



YouTube

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

Reality: Content Recommendation Marketplace

Content creator

YouTube

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

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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***

Content creator

mmendations.

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.
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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