The Long-Term Consequences of Recommendation

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Introduction & Hypothesis

User Steering in Recommendation Systems

- Recommendation systems are important for the digital economy
- Exposure to the right kinds of content is convenient for users, and makes them learn about quality
- Also/However:

  > *"To require that internet platforms give users the option to engage with a platform without being manipulated by algorithms driven by user-specific data."*
  > *—Proposal for a Filter Bubble Transparency Act, S. 2024*

- Question: Does exposing users to a particular kinds of content increase their likelihood of watching this content when shown in the future?

Overview of the First Part

Introduction & Hypothesis

Intervention: Using Non-Personalized Recommendations

Empirics

Conclusion

Related Literature

- Theory: Two reasons for diverting search: More total time on platform for consumers, and influence on strategic choices of firms Hagiu et al. 2011
- Distinguishing exposure and informational effects on Movielens Aridor et al. 2022
- Engagement-diversity tradeoff Holtz et al. 2020; Nguyen et al. 2014
- Null effects regarding the effect of exposure to opposing political views Levy 2021 and Russian misinformation Eady et al. 2023

Intervention: Using Non-Personalized Recommendations

Considerations When Intervening into Recommendations

1. Many platforms that are easy to interact with don't have ecosystem validity
2. Using recommendations from platforms without being able to control for their algorithms may bias recommendations
3. Credible inference needs high-quality recommendations
4. Contractual relationships lead to legal questions

Variation in Content Categories

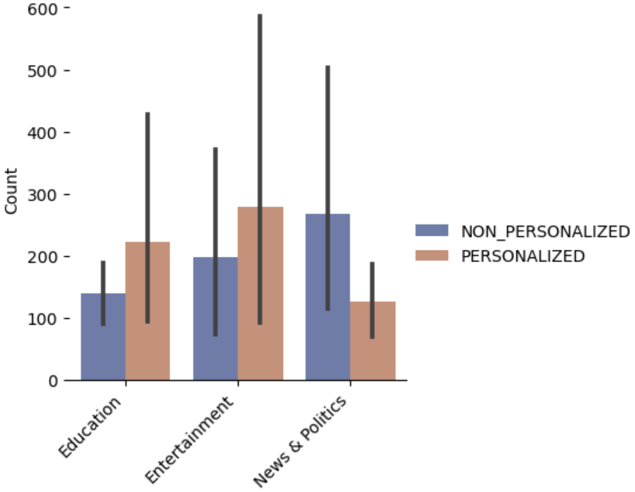

Figure: Content Categories Recommended in Software Test. Bands show two standard deviations.

Idea for a Class of Interventions: Use Non-Personalized Content

- General requirement by platforms to offer non-personalized recommendations in Europe coming next spring:

  > *"[P]roviders of very large [...] recommender systems shall provide at least one option [...] which is not based on [personalization]." Digital Services Act, Art. 38*

- Idea: Use non-personalized content to introduce variation into recommendations, potentially using additional information
- Fundamental limitation: Can only use browser extensions, no apps. ($\hookrightarrow$ CMA: "Open Standards")

Timeline of an intervention

1. User signs up and installs the app, is assigned to treatment or control group
2. Users use the app for an initial, purely observational, period
3. After this, during an interventional period, whenever a user visits a page on Youtube.com:
   - Browser opens a second, invisible, incognito window
   - Browser downloads this content, and extracts the site html,
   - Browser extracts additional metadata on videos, in particular “content category” and views
   - Changes the html of the original page (either introducing incognito, original content), or not

   and serves the resulting main page.

For the rest of this talk: Consider treatment that includes two additional pieces of a video of category “news”.

Empirics

Data

Pilots Pilots of $n = 20$, then another study with $500 \leq n \leq 1000$ participants.

Recruitment Via Youtube ads.

Timing All users start the experiment at the same time.

Controls Intake survey elicits sociodemographic information, and asks for data exports of viewing history for extra payment.

Qualitative Questions Intake and leaving survey asks for questions on sentiment towards the platform and the diversity of consumption.

Estimand

We are interested in two main estimands:

- In week $t = 1, 2, \ldots, 10$, how many videos did the user watch on estimate consumption controlled for exposure Y_t and position on the page?

$$Y_{it} = \alpha_i + \lambda_t + v_{it}$$

- In week $t = 1, 2, \ldots, 10$, how many videos did the user watch on Youtube C_t?

Imperfect Randomization

The randomization of videos is imperfect in at least three ways:

1. The personalized videos change in response to the change in recommendation: We cannot control for the “algorithm state” DAG
2. A second source of bias comes from the user preferences being correlated with the incognito content; fix: Control for zip code-level properties
3. The selection will be based on relatively coarse features of videos video category examples; unobservable quality of videos can be correlated with appearance in personalized recommendations

Getting Sufficient Statistical Power

- Insight from industry professionals: Relative effect sizes/clickthrough rates of 1-3% are usual
- Depending on heterogeneity on the platform, this means potentially high number of participants needed (difference to work inside of platforms)
- Treatment of users where treatment is quite small: adaptive design.

Identifying Mechanisms for Change

- Two main channels in Economics literature: Bringing items into consideration set, and making users learn about video quality.
- In recommmendation systems literature and quantitative marketing: Behavioral effects.
- Research design in the style of Aridor et al. 2022 to elicit preferences of users for content is possible, but it seems hard to reject that users are Bayesian in this model.

Conclusion

Conclusion

- Preparing a field experiment on the long-term consequences of recommending news
- Using recommendation systems and interoperability regulation for new type of intervention: Use non-personalized recommendations as pool of content to select from for an intervention
- Intend to estimate dynamic treatment effect and identify mechanisms

Next steps:

- Receive IRB Decision
- Start 1-month pilot with users
- Finalize estimation of mechanisms theory

And now over to amazon.com!

References I

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[3] Andrei Hagiu et al. "Why do intermediaries divert search?" In: *The RAND Journal of Economics* 42.2 (2011), pp. 337–362.

[4] David Holtz et al. "The engagement-diversity connection: Evidence from a field experiment on spotify". In: *Proceedings of the 21st ACM Conference on Economics and Computation*. 2020, pp. 75–76.

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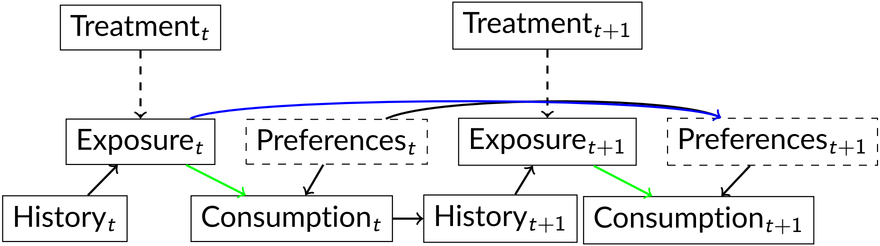
DAG

Back



Treatment$_t$
Treatment$_{t+1}$
Exposure$_t$
Preferences$_t$
Exposure$_{t+1}$
Preferences$_{t+1}$
History$_t$
Consumption$_t$
History$_{t+1}$
Consumption$_{t+1}$

video category examples

Back

News, Entertainment, Sports; views, channel, length