Can online behavior predict political attitudes?

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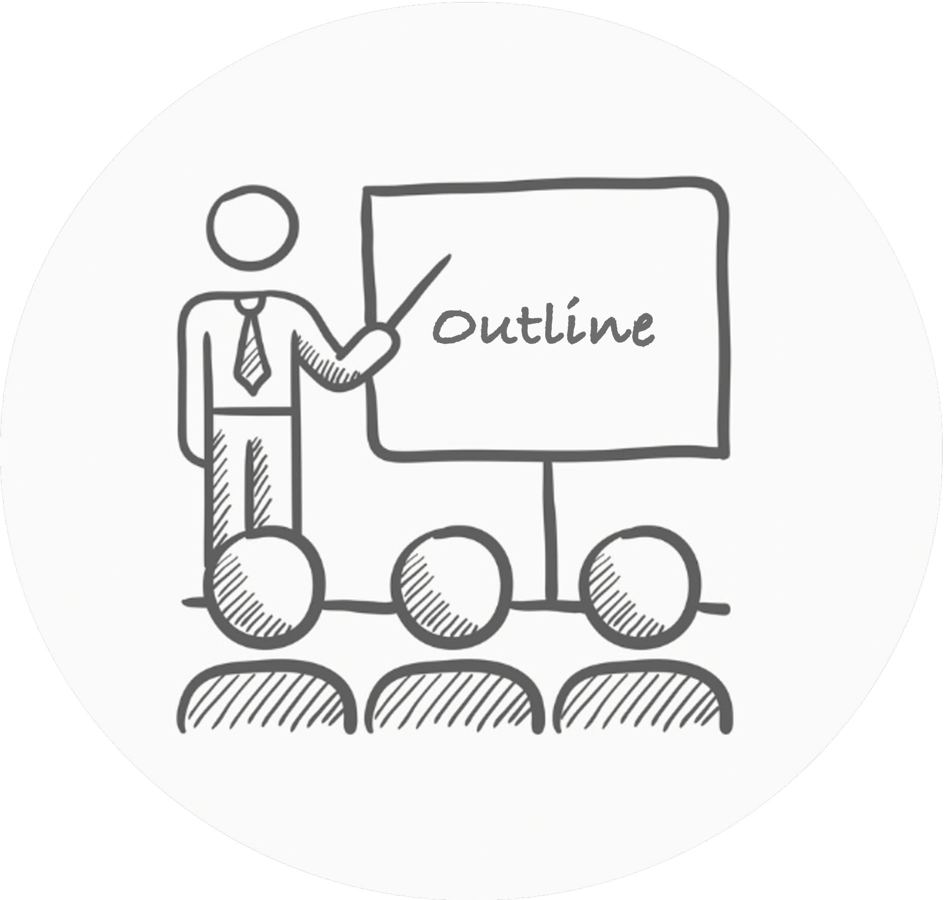
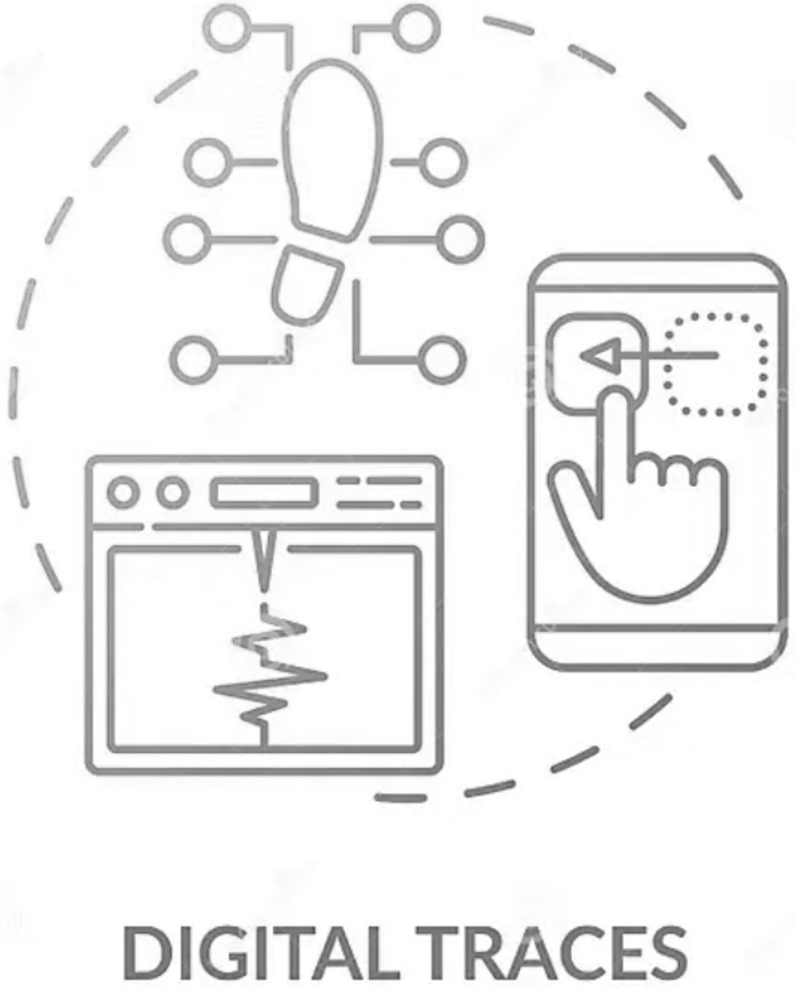


Background

- *Methodological perspective:* increased use of digital trace data in social sciences
- *Substantive perspective:* relationship between online browsing and political orientation

Our research

- Predicting self-reported political orientation using browsing data



- Recent increased interest in the social sciences
- Considered an attractive alternative to surveys
  - Superior quality
  - Allow to overcome limitations
- Have limitations that are often ignored
  - Representativeness
  - Demographics, attitudes, beliefs have to be inferred

- Increased interest in predicting individual level characteristics
  - Focus on social media or media consumption
- Predicting demographics
  - Overall high accuracy (e.g, gender or age)
- Predicting attitudes, opinions, beliefs…
  - More mixed picture

Relationship between what people read online and their political orientation

- Confirmation bias
- Echo chambers
- Filter bubbles

Can we predict political orientation using information on websites visited and apps used?

- Outcome: political orientation - *from survey*
- Predictors: categories of websites browsed, and apps used - *from tracking apps*
- Machine learning approach

Non-probability online panel in Germany

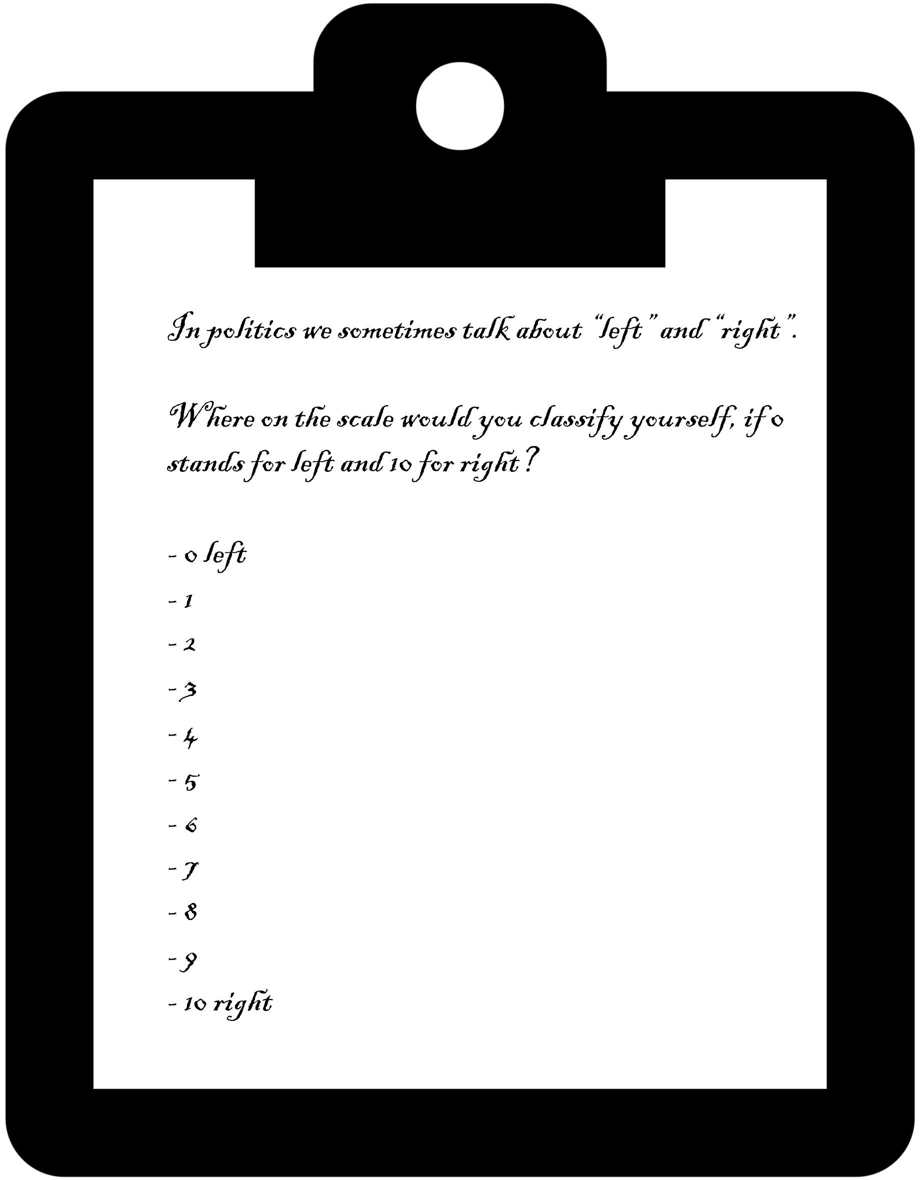
- N=2,100
- Survey with three waves around September 2021
- Tracking app installed on PC and/or mobile device
- > 600 respondents had both PC and mobile tracked

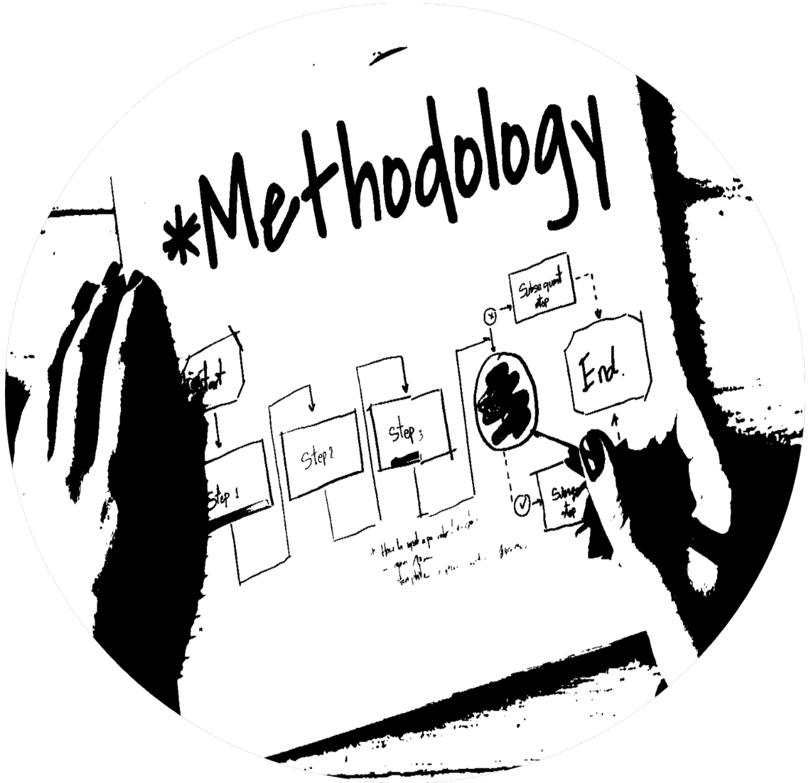
Survey

- 11-point Likert scale asking about political orientation

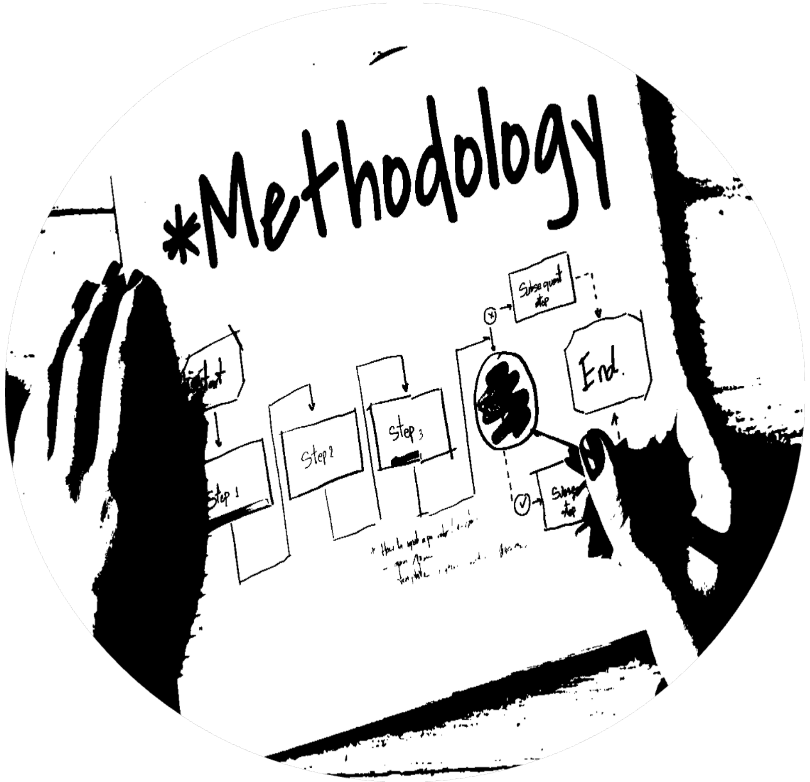
Tracking app

- Mobile, PC, or both
- Total period up to 6 months (Jul – Dec ‘21)
- Information used on domains browsed on PC/mobile and apps used on mobile





- Classification of web domains and apps using ChatGPT
- Looking at usage from PC & mobile separately
- Two operalizations of usage: count and duration



Machine learning approach

- Random forest
- 70% of sample used to train model
- 30% of sample use to validate predictions

Baseline model (age, gender, immigration status, edu) vs. tracking | baseline & tracking

Baseline model

$MSE_{SD} = 1.91$

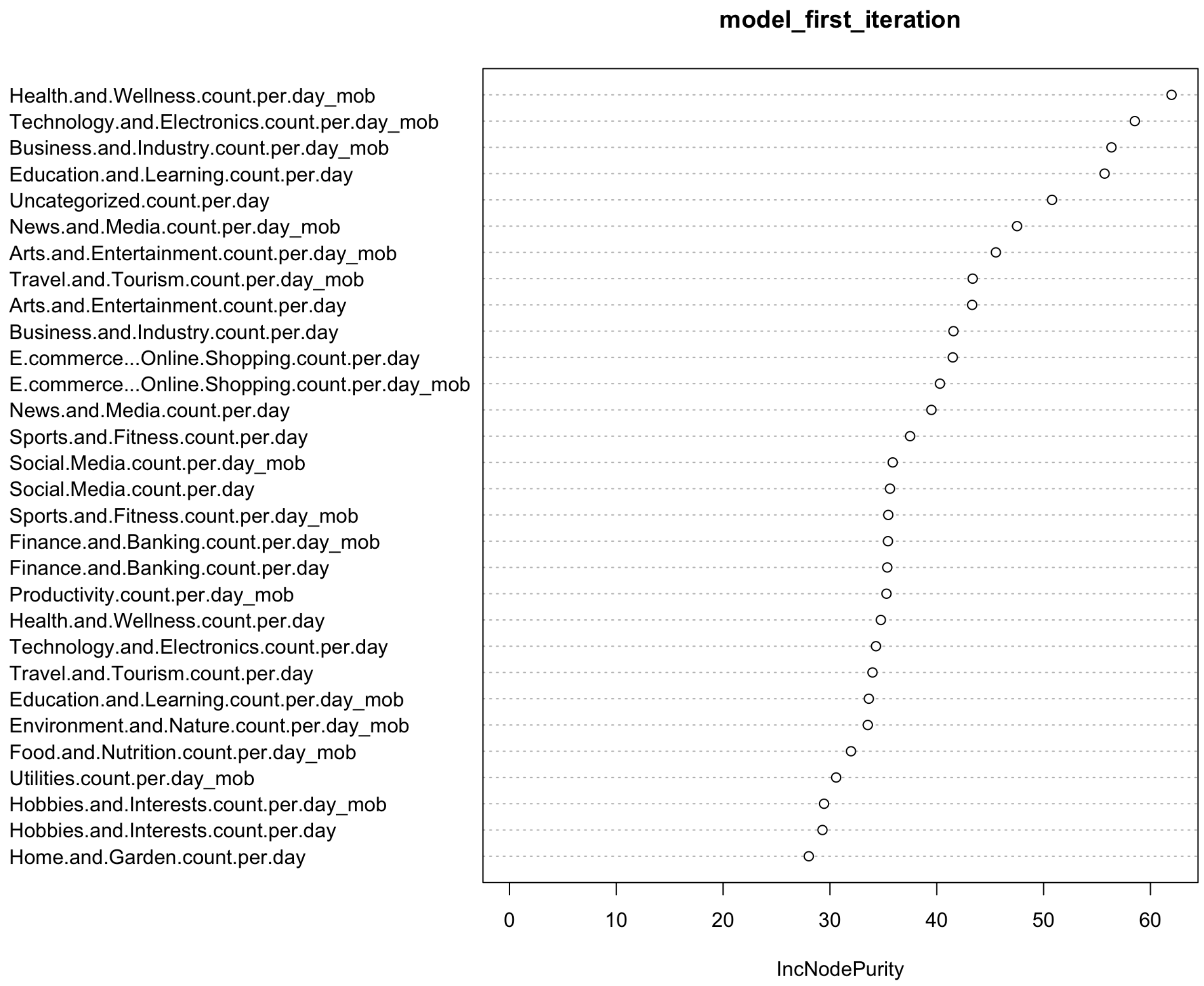
Count/duration per day (mobile & PC)

$MSE_{SD} = 1.89$

Baseline & duration/count (mobile & PC)

$MSE_{SD} = 1.91$

Differences statistically **insignificant**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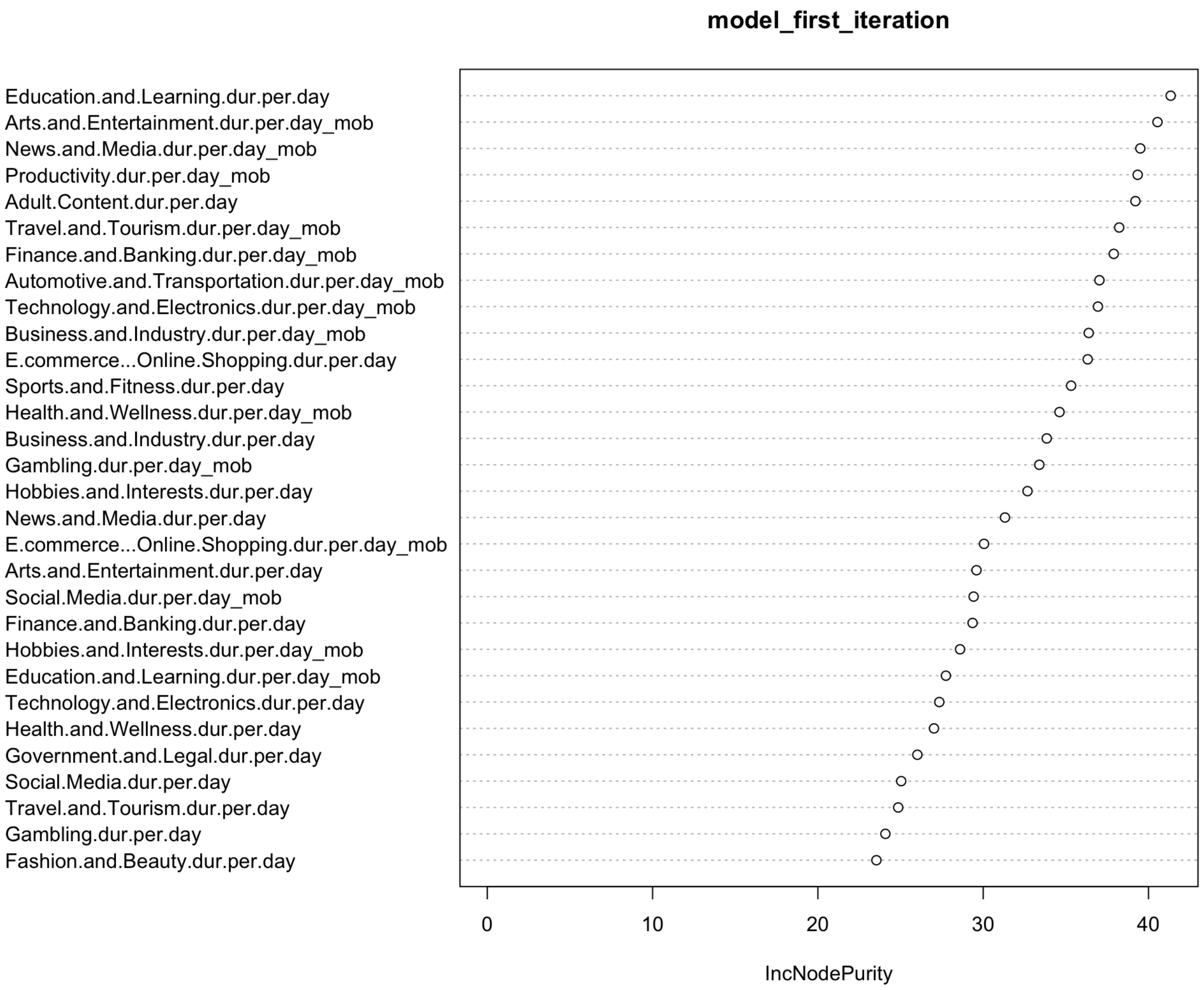
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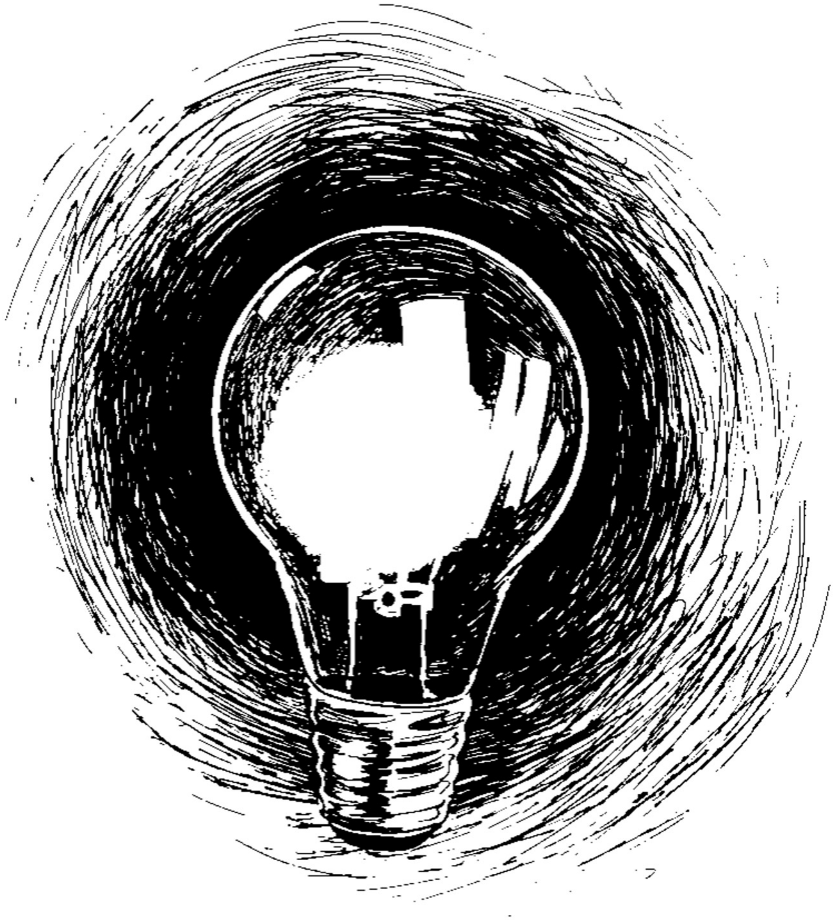

Conclusions

- Adding tracking data does not improve political orientation prediction
- Prediction accuracy using tracking data only similar to basic demographics only
- Better classification of domains and apps and more diversity in outcome might improve prediction accuracy

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Thank you!

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