Inescapable Bias: The Role of Recommender Systems in Social Media Radicalization

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Motivation

- Social networks are ubiquitous: socializing, reading news, expressing ourselves
- The public wants to know what role their platforms might have in radicalizing users, specially younger ones
  - Mainly anecdotal evidence (e.g. Facebook depression experiments, YouTube's bizarre videos aimed at kids, etc.)
- Journalists and specialists alike argue that social media's algorithms are tuned to peddle conspiracy theories, extremist views, and false information
- The debate around the role of recommender systems in social media radicalization is still too recent and based in anecdotes
- More quality research is vital to inform both the public and opinion makers about if and how much recommendation algorithms influence social media users

Literature Review

- F. Ricci, L. Rokach, and B. Shapira, "Recommender Systems Handbook"
- Z. Zhao et al., "Recommending what video to watch next: a multitask ranking system"
- A. Sîrbu, D. Pedreschi, F. Giannotti, and J. Kertész, "Algorithmic bias amplifies opinion fragmentation and polarization: A bounded confidence model"
- A.-A. Stoica, C. Riederer, and A. Chaintreau, "Algorithmic Glass Ceiling in Social Networks: The effects of social recommendations on network diversity"
- M. H. Ribeiro, R. Ottoni, R. West, V. A. F. Almeida, and W. Meira, "Auditing radicalization pathways on YouTube"
- C. Roth, A. Mazières, and T. Menezes, "Tubes and bubbles topological confinement of YouTube recommendations"

Proposal

- How social networks recommend content to users is relevant to recent waves of political polarization and radicalization
- Most of the algorithms currently employed by social media companies are trade, and subject to constant experimentation and tuning
  - E.g., YouTube has over 2 billion monthly logged-in users, but it makes no significant effort to clarify changes made to the algorithm
  - Most of the developing world still isn't impacted by policy changes
- The goal is to understand how their algorithmic design might foster confinement dynamics in the "phase space" of recommendations
  - Do recommendation algorithms always create "filter bubbles", suggesting ever more engaging videos about a certain topic?

MovieLens

- The main dataset used for experimentation was MovieLens
    - F. M. Harper and J. A. Konstan, "The MovieLens Datasets: History and Context"
    - A well-known set of movie reviews
- 25M ratings applied to 62K movies by 162K users, enriched with information about the movies' credits, metadata, keywords, and links
    - A sample of 30,689 movies was taken in order to reduce the harware requirements of iterative experimentation

Book-Crossing

- The dataset used to validate hypotheses was Book-Crossing
    - C.-N. Ziegler, "Book-Crossing Dataset"
    - A well-known set of book reviews
- 1.1M ratings applied by 278K users to 271K books, and information like title, author, publisher, etc.
    - A sample of 20,000 books was taken in order to reduce the harware requirements of iterative experimentation

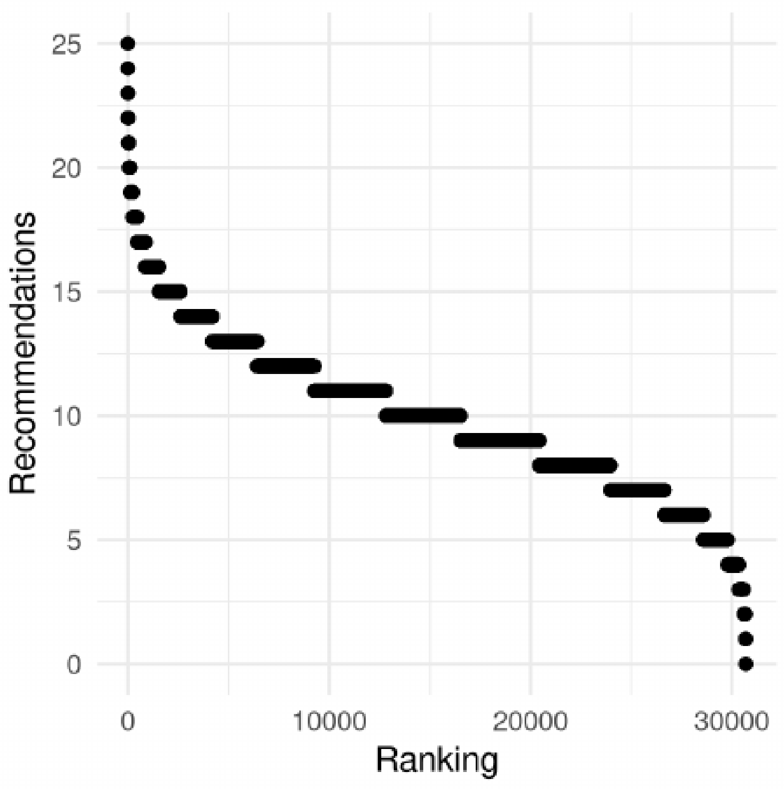
Techniques

- Excluding user information is important because they might transfer their own biases to the model
  - Content-based recommender: able to identify similar items based on their metadata and suggest the closest items
  - Create a vector representation of each item and then use a similarity metric to recommend the most similar items to the one in question
- "Recommendation profiles": a summary of how many times an arbitrary item is recommended overall
  - The algorithm is asked to return the top-n most similar items to the input according to its internal metric, and this is repeated for every item
  - The number of times each item showed up in the top-n most similar items

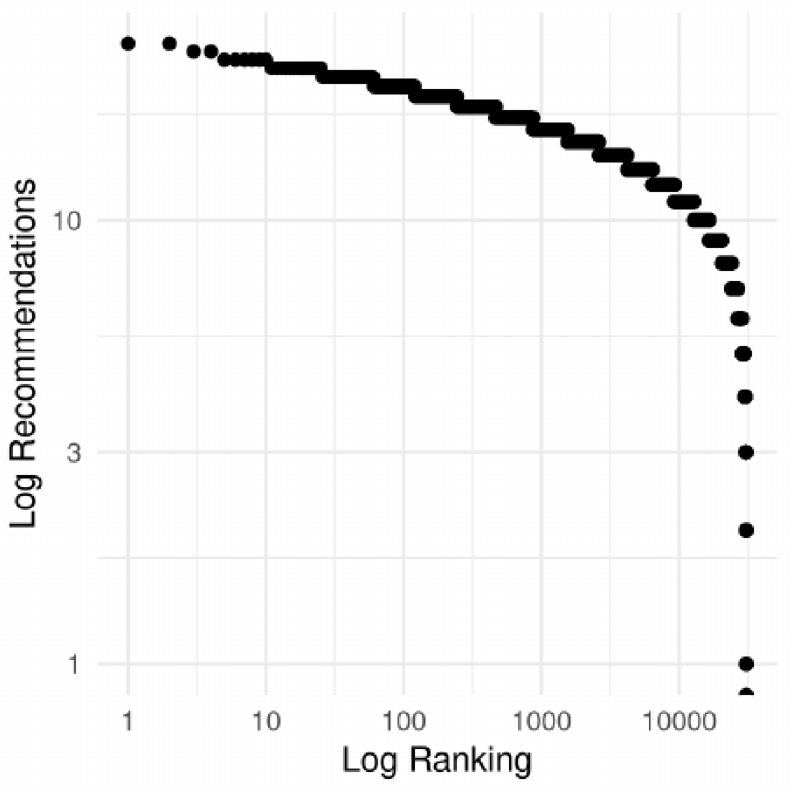
Techniques (cont.)

- "Trivial model": a simple sampler that returns n movies at random when asked for a recommendation
- "Vanilla model": generated vector representations for the MovieLens dataset, without any modifications
  - Each position represented one of the words of the corpus, and each element indicated how many times that word appeared in the metadata
  - The internal metric used, by default, was cosine similarity
- "Sparse model": representations were based on fictional metadata that were comprised of words sampled at random from the full corpus
  - The sparser the vectors, the higher the odds of the recommendation curve displaying a steep left-hand side

Preliminary Results

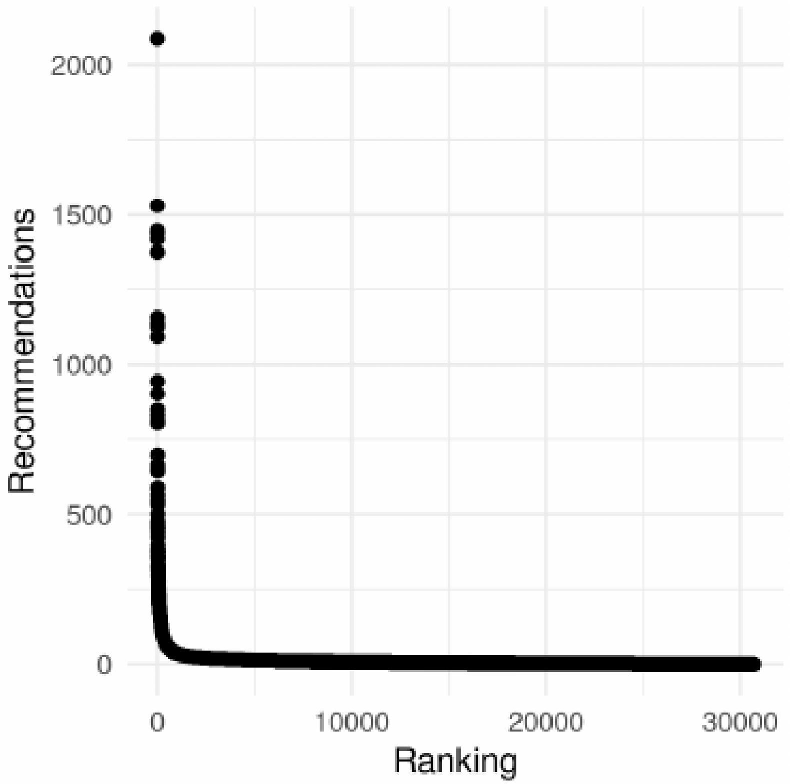


(a) *Trivial recommendations.*

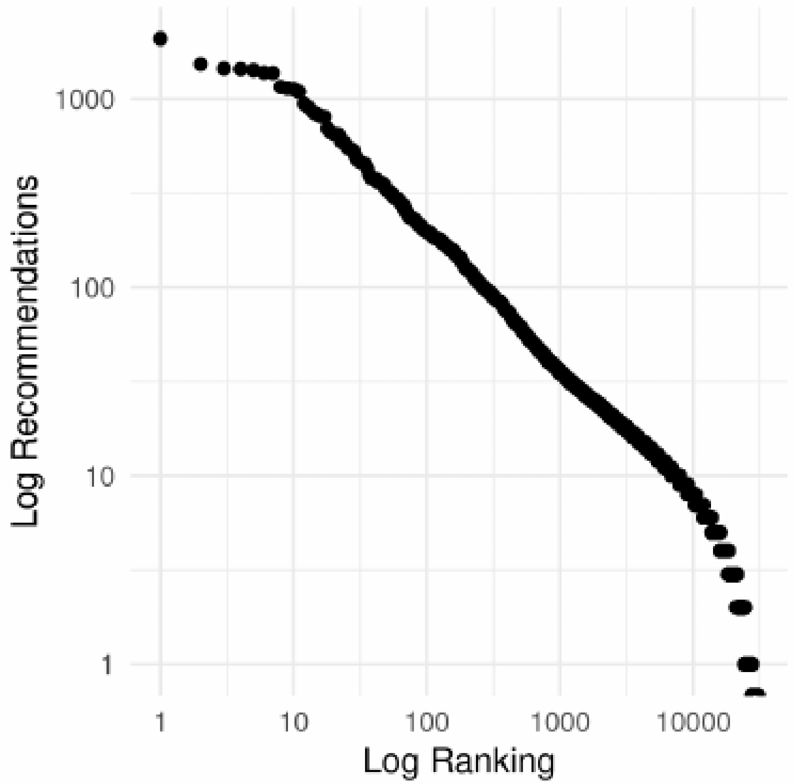


(b) *Log-log plot.*

Preliminary Results (cont.)

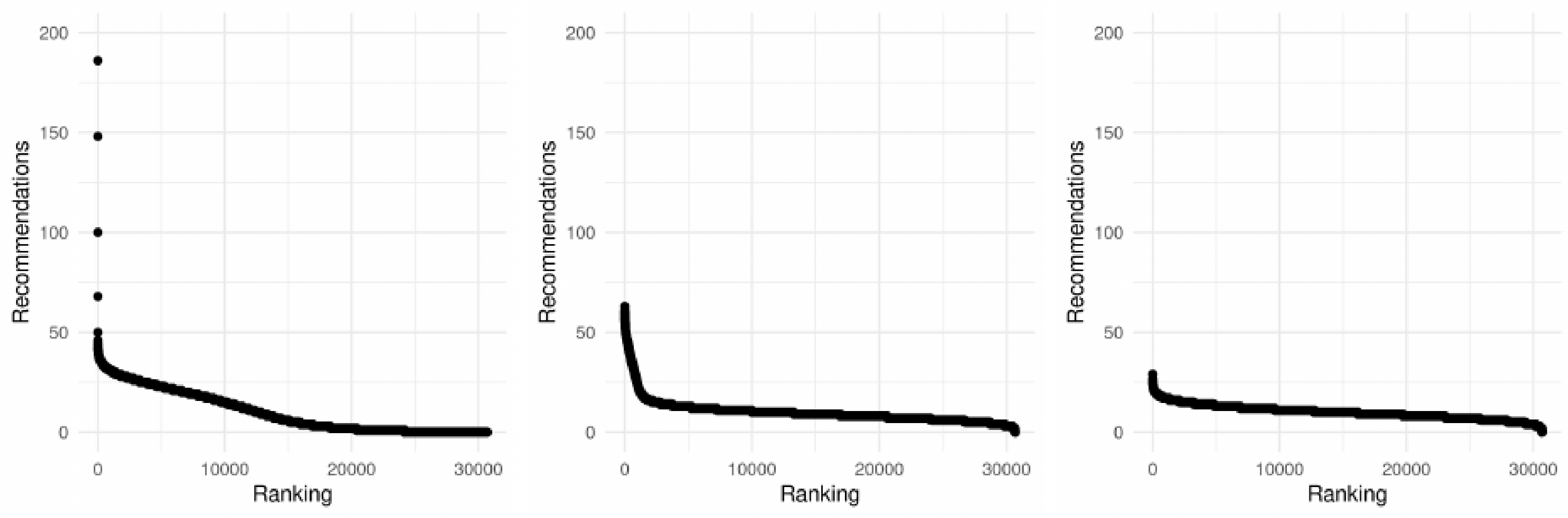


(a) *Rec. based on movie metadata.*



(b) *Log-log plot.*

Preliminary Results (cont.)



(a) $P(w_i) = 1 \times \overline{P(w)}$.

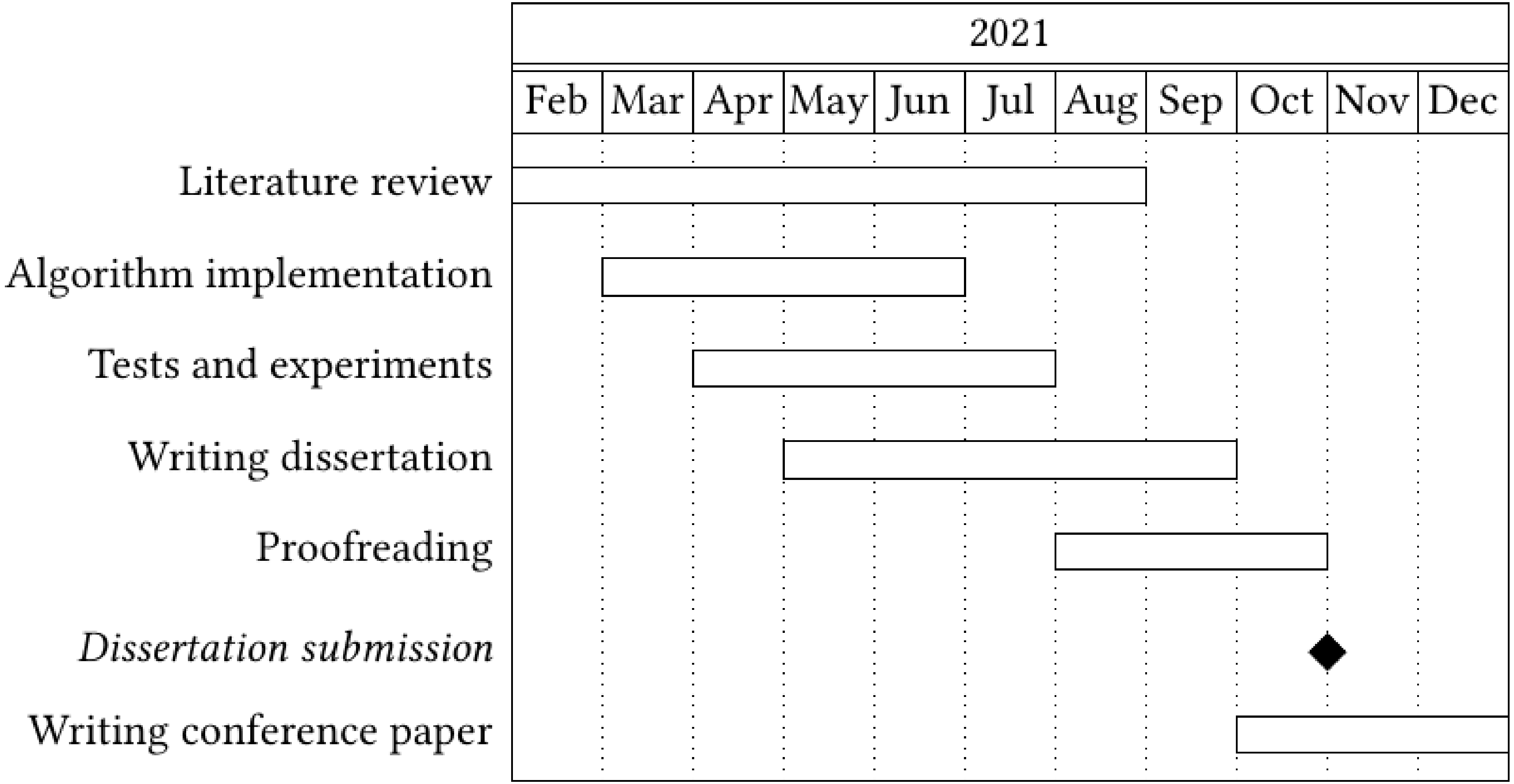
(b) $P(w_i) = 10 \times \overline{P(w)}$.

(c) $P(w_i) = 100 \times \overline{P(w)}$.

Discussion

- More experiments are still necessary in order to identify exactly what is the nature of the bias detected
  - What movies are the most recommended in each case and whether the subset of top-recommended movies is roughly consistent
- Using Google’s newly released TensorFlow Recommenders it might be possible to gather data about what happens as users follow suggestions
  - Goal: determining if the model's dynamic increases or decreases the exponential profile of recommendations
- Showing that that these algorithms are suggesting a subset of items exponentially more than the rest could be one more piece evidence
  - Are these social networks are creating filter bubbles that radicalize users?

Schedule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Algorithm implementation
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Proofreading
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