BIAS IN RECOMMENDER SYSTEMS – EVALUATION AND MITIGATION

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OUTLINE

- Introduction to Recommender Systems
- Evaluation of RS
- Bias in RS
- Feedback Loops
- Mitigation Measures
- Indicative Example
- Other considerations

RECOMMENDER SYSTEMS

RECOMMENDER SYSTEMS

- Software tools that recommend items that can prove useful to the users
- They filter the available data in the web, based on the needs and the preferences of the users
- To achieve an efficient filtering and satisfactory recommendations, several pieces of information are necessary about the past behaviour of the users, their attributes, information about similar users, the attributes of the items etc.
- They act as a personalized filter for each user, mitigating information overload for the user

RECOMMENDATION TECHNIQUES

- Content based
- Collaborative filtering
- Hybrid

EVALUATION

- **Accuracy**

- Coverage
- Diversity
- Fairness
- Novelty, Serendipity, Unexpectedness

- Demographic Parity

BIAS IN RECOMMENDER SYSTEMS

EXAMPLES OF BIAS IN RS

- **Google's online advertising** system displays ads for high-income jobs to men much more often than it does to women (Edizel et al., 2019)
- **Google ads** related to arrest records are significantly more likely to show up on searches for distinctively black names or a historically black fraternity (Edizel et al., 2019)
- **Instagram →** negative effects in the psychology of adolescent girls(Milmo, 2021)
- **Facebook:**
  - Responsible for increasing violence in developing countries as it promotes polarized content over neutral one (Milmo, 2021)
  - **>33% of** Facebook groups for German politics showcase increasing volumes of extremistic content (J. Horwitz, 2020)
  - **64%** of participants in the aforementioned groups they became members due to facebook's recommender system (J. Horwitz, 2020)
- **Amazon:**
  - The number of books that are against vaccination is double the number that are vaccination friendly
  - There is a tendency in reinforcing users' belief. (Shin and Valente, 2020)

TYPES OF BIAS IN RECOMMENDATIONS

Bias towards users

- Bias related to Fairness and discrimination

Bias towards items

- Data Bias
- Selection Bias
- Exposure Bias
- Conformity Bias
- Position Bias
- Inductive Bias
- Popularity Bias

FEEDBACK LOOPS

Data biases would incur or intensify the data imbalance, exacerbating bias issues in recommendation results (Data bias ⟶ Data imbalance ⟶ Bias in Results); while the biased recommendations would in turn impact the decisions, exposure, and selections of users, reinforcing the biases in users' future behaviors (Bias in Results ⟶ Data Bias).

Chen et al, 2023

MITIGATION MEASURES

DEBIASING TECHNIQUES (USER ORIENTED BIAS)

- Setting fairness thresholds depending on the definition of fairness in the problem at hand
- Increasing diversity in content
- Increasing serendipity

- Demographic Parity
- Rebalancing
- Regularisation

CHALLENGES

- Data privacy
- Trade offs
- Complexity

DEBIASING TECHNIQUES (ITEM ORIENTED BIAS)

- Setting thresholds for item coverage
- Increasing diversity of users to whom the items are recommended
- Recommend items from the long tail

- Data Imputation
- Sampling
- Reinforcement Learning

EXAMPLE – FAIRNESS ACROSS ITEM PROVIDERS IN RS IN TERMS OF COVERAGE AND DIVERSITY PER ITEM

- Main objectives of item providers are
  - Maximisation of users to whom provider's items are recommender (coverage)
  - Maximisation of diversity of these users (diversity)
- Problem's objective is to provide a fair distribution of recommendations, so that providers are at least to some extent satisfied about the aforementioned metrics (Koutsopoulos, et al., 2021), (Karakolis, et al. 2022)

EXAMPLE – FAIRNESS ACROSS ITEM PROVIDERS IN RS IN TERMS OF COVERAGE AND DIVERSITY PER ITEM – THE PROBLEM

- Optimisation problem, maximization of total estimated rating of items, or minimization of the cost (distance from a baseline solution without fairness considerations)
- Subject to:

  Cov(p) >= Kp

  $\overline{\mathrm{Div}(p)}$**>= Dp**

- **Kp**: η ελάχιστη μέση κάλυψη για τα αντικείμενα του παρόχου p
- **Dp**: Η ελάχιστη μέση κανονικοποιημένη διαφοροποίηση για τον πάροχο p.

EXAMPLE – FAIRNESS ACROSS ITEM PROVIDERS IN RS IN TERMS OF COVERAGE AND DIVERSITY PER ITEM - APPROACH

- Create a baseline solution through collaborative filtering without any restrictions
- Solve the problem subject to coverage constraints (linear programming)
- Find a solution for the diversity constraints (NP-complete problem), needs heuristic solution

OTHER CONSIDERATIONS

- Transparency, explainability, accountability
- Continuous monitoring
- Multistakeholder Recommender Systems
- Mitigation of polarization
- More control to the users