Holistic AI × The Alan Turing Institute

Bias in Recommender Systems Part II

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Contents

II – Fairness in Recommender Systems

- 1) Introduce Taxonomy of fairness is Recommender setting.
- 2) Study Examples from the introduction through these new lenses.
- 3) Motivate the need to measure bias in Recommendation.

Taxonomy

- Recommender system fairness can be explored from a variety of different perspectives.
- These can be broadly split into:
  - **user fairness.**
  - **item fairness.**
- Some approaches take into consideration both user and item fairness.

Item Fairness

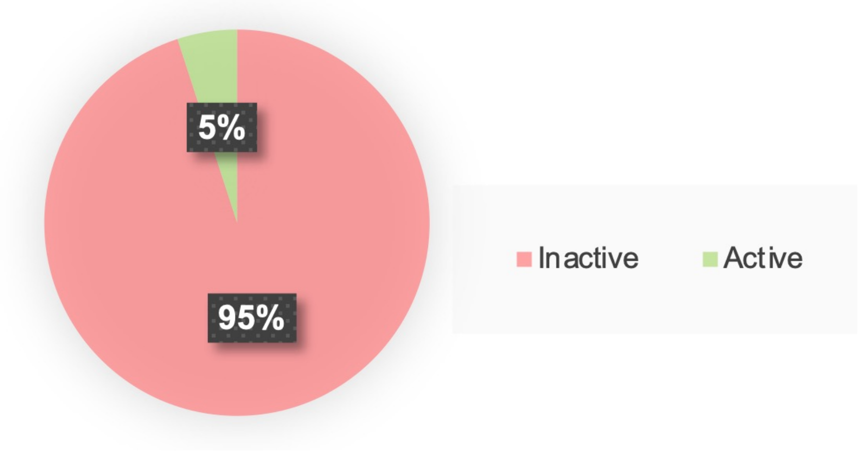
- Item fairness attempts to ensure that all items are given the same chance.
- We can further divide this into
  - **individual item fairness.**
  - **provider fairness.**
- Individual item fairness looks at all items individually, while provider fairness looks at groups of items that belong to the same provider and attempts to ensure fairness at an aggregate level.
- For instance, an item could be a specific cereal box, while the provider is a brand of cereals (e.g., Kellog's).

User Fairness

- User fairness attempts to ensure users are exposed to similar items.
- Once again there is
  - **individual user fairness.**
  - **group user fairness.**
- User group fairness ensures that different subgroups of the population (e.g., male / female) are shown similar items.
- User individual fairness ensures fairness by attributing similar items to similar users. So sensitive attributes don't drastically change results.

Activity Fairness

- One risk for recommender systems is for them to work better for the most active users
- This is usually a small minority of the total user base



Example 1: Item Provider Fairness

- Recall Example 1 from the introduction, we have an E-Commerce company that recommends items to consumers, but it is also a provider of items on its platform (e.g., Amazon).
- This E-Commerce company is incentivized to recommend its own products more frequently than other provider’s products.
- Not only is this unethical, but it is also illegal in some cases, hence the importance of measuring such bias.
- This question was addressed in Dash et al, 2021.

Example 2: User Group Fairness

- Recall Example 2 from the Introduction, we have a job browsing and recommendation website, that weekly recommends jobs to its users.
- Historically, male users were a lot more likely to be interviewed for high paying jobs, and their recommendation engine will more likely than not have learnt that bias.
- Hence the importance of measuring user group fairness, to start changing the patterns of the past.
- This question was addressed in Imana et al., 2021.

Example 3: Individual Item Fairness

– Recall Example 3 from the Introduction, we have a hotel recommendation app that gives lists of possible hotels based on searches of users.
– Recommendation engines often get caught in the trap of recommending the most popular items more, so some hotels might be getting almost no exposure.
– Hence the importance of measuring individual item fairness, to make sure every item gets a chance.
– This question was addressed in Sun et al., 2019.

Example 4: Activity Fairness

- Recall Example 4 from the Introduction. We have a movie streaming website that recommends movies to its users
- Recommendation engines often work better for the most active userbase which is a small proportion of users
- Hence the importance of checking the activity fairness.
- This question was addressed in Li.Y et al, 2021

Static and Dynamic Fairness

– Until now, we have only talked about recommender systems as Static models, with one training set and one set of predictions.
– However recent improvements in recommender systems make the training dynamic, in the sense that the recommendations evolve with the user’s evolving interests.
– Dynamic Fairness extends this dynamic training to take into account fairness considerations. So that the fairness is ensured at each retraining.

How to measure bias?

– As we have seen from the examples, there are many different types of fairness issues that can arise in recommendation.
– We need ways of measuring these fairness notions quantitatively so we can help in spotting these issues and then mitigating them.
– We will look at measuring and mitigating bias in the next sections of the course.

Conclusion

- We have given an introduction to the taxonomy around fairness in recommendation
- We have studied a few examples through these new fairness lenses
- We have motivated the need to measure bias in recommendation settings.

Next

- Part I – Introduction to Recommender Systems
- Part II – Fairness in Recommender Systems
- **Part III – Measuring Bias in Recommender Systems**
- Part IV – Mitigating Bias in Recommender Systems

References

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