

The Alan Turing Institute

Bias in Recommender Systems Part III

Content by: Sachin Beepath, Giulio Filippi, Cristian Munoz, Roseline Polle, Nigel Kingsman, Sara Zannone

Speaker: Giulio Filippi



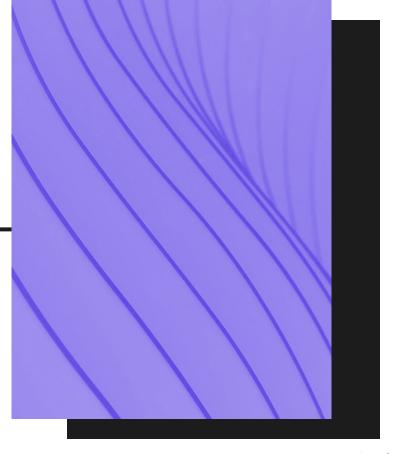
Contents

- 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



III – Measuring Bias in RecommenderSystems

- 1) Introduce metrics for user and item sides of bias.
- 2) Give some examples to help the students understand the metrics.
- 3) Show how we can compute these metrics with the holistical library





Exposure distribution

– We first define the exposure distribution. The exposure distribution p_A of a group A is defined as

$$p_A(i) = \frac{N_A(i)}{N_A}$$

- Where $N_A(i)$ is the number of times item i is shown to group A and N_A is the total number of items shown to group A.
- The exposure distribution acts as an empirical probability of a group being shown each item.



Exposure distribution (example)

- We have two groups of users A and B and items 1, 2, 3.
- Group A is shown items 1, 2 and 3 respectively 1, 2 and 3 times.
- Group B is shown items 1, 2 and 3 respectively 2, 2 and 2 times.
- The exposure distribution for group A is then [1/(1+2+3), 2/(1+2+3), 3/(1+2+3)]
- The exposure distribution for group B is then [2/(2+2+2), 2/(2+2+2), 2/(2+2+2)]



User group fairness metric 1

- We want to measure whether the recommender system recommends items evenly to different groups of users.
- The Exposure Total Variation measures the total variation distance between the exposure distribution for groups A and B (e.g., male / female).
- Total Variation = $\frac{1}{2}\sum_{items\ i} |p_A(i) p_B(i)|$
- The value of the metric ranges between 0 and 1 with 0 indicating an exact match and 1 indicating the distributions are as distant as they can be.

TOT VAR (example)

- Suppose there are 5 items. And we have computed the exposure distributions as $p_A = [0.1, 0.1, 0.1, 0.1, 0.6]$ and $p_B = [0.2, 0.2, 0.2, 0.2, 0.2]$
- The total variation distance is
- $Total\ Variation = \frac{1}{2}(4 * |0.1 0.2| + |0.6 0.2|) = 0.4$
- 0.4 is a relatively high total variation, so this data is considered biased.



User group fairness metric 2

 The Exposure KL is the Kullback Leibler divergence from the item exposure distribution of group A to that of group B.

$$- KL Div = \sum_{items \ i} p_A(i) log \frac{p_A(i)}{p_B(i)}$$

- The KL doesn't work well if there are items that are not shown to group
 B.
- On the other hand, it is widely used in theoretical work, and an important metric to know about.



KL DIV (example)

- Suppose there are 5 items. And we have computed the exposure distributions as $p_A = [0.1, 0.1, 0.1, 0.1, 0.6]$ and $p_B = [0.2, 0.2, 0.2, 0.2, 0.2]$
- The Kullback-Leibler Divergence is

$$- KL Div = 4 * 0.1 * \log\left(\frac{0.1}{0.2}\right) + 0.6 \log\left(\frac{0.6}{0.2}\right) = 0.3819$$

Note: interpreting KL DIV is not always easy, except in relative terms.



Individual Item fairness metric 1

- The aggregate diversity is the proportion of all items that have been recommended to at least one user.
- $Agg Div = \frac{1}{|I|} \sum_{items \ i} 1[item \ i \ is \ shown]$
- We want the aggregate diversity to be close to 1, indicating almost all items are shown at least once.
- If the aggregate diversity is low, then a large proportion of items are not even given a chance.



AGG DIV (example)

- Suppose there are 10 items. And we have computed the item exposure distribution as p = [0.1, 0.1, 0.1, 0.1, 0.6, 0, 0, 0, 0].
- What is the aggregate diversity?
- As is seen from the distribution, 5 out of 10 items have nonzero probability of being shown.

- So
$$Agg \ Div = \frac{5}{10} = 0.5$$



Individual Item fairness metric 2

- The gini index is a measure of how unequal a distribution is. We apply it to the exposure distribution of items.
- Suppose we have the overall exposure distribution q, and we sort items so that so that $q(i_k)$ increases with k.

$$- GINI = \frac{1}{|I|-1} \sum_{k=1}^{|I|} (2k - |I| - 1)q(i_k)$$

 An algorithm that recommends each item the same number of times (uniform distribution) will have a Gini index of 0 and the one with extreme inequality will have a Gini of 1.



GINI (example)

- Suppose there are 4 items. And we have computed the item exposure distribution as p = [0.1, 0.2, 0.3, 0.4]. (Note: this is sorted in increasing order).
- Applying the formula from previous slide

$$- GINI = \frac{1}{3} [(-3)0.1 + (-1)0.2 + (1)0.3 + (3)0.4 = \frac{1}{3}$$

1/3 is a low gini index, so data is quite fair.



Individual Item fairness metric 3

- The average recommendation popularity stands true to its name, it measures on average how 'popular' is a recommendation.
- Let i_{uj} be the jth item (of K) recommended to user u. Let $N(i_{uj})$ be the total number of times this item appears in the training set.

$$- AVG REC POP = \frac{1}{|U|} \sum_{i} u_{K}^{1} \sum_{j=1}^{K} N(i_{uj})$$

 High values of this metric imply that on average we are recommending very popular items. Lower values are considered fairer.



AVG REC POP (example)

 Suppose there are 3 users and 3 items, with the following prediction matrix

$$M = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

Item 1 is recommended 3 times, item 2 is recommended twice, item 3 is recommended once.

$$- AVG REC POP = \frac{1}{3} \left[\frac{1}{3} (3 + 2 + 1) + \frac{1}{2} (3 + 2) + 1(3) \right] = \frac{15}{6} = 2.5$$

 Note: there is no scale for this metric, one must interpret it relatively or as a fraction of the maximum popularity.

Computing Bias Metrics with holistical library

- When computing recommender systems bias metrics with the holistical library, we first need to understand the type of data we input.
- The input mat_pred is a matrix that contains a 1 for each (user, item) pair where the item is recommended to the user.
- The documentation of all the recommender bias metrics can be found here.



Computing Bias Metrics with holistical library

The first step is installing the library



Once the library is installed, import the desired metric.

```
from holisticai.bias.metrics import aggregate_diversity
aggregate_diversity(mat)

Python

from holisticai.bias.metrics import gini_index
gini_index(mat)

Python
```

Compute the value as shown above.



Computing metrics in batch with holistical library

 There is also a helper to compute all bias metrics in batch. Suppose we are interested in all item-based metrics. We can compute them as follows.

```
from holisticai.bias.metrics import recommender_bias_metrics
recommender_bias_metrics(mat_pred=mat, metric_type='item_based')
Python
```

The output is a pandas DataFrame, e.g.,

	Value	Reference
Metric		
Aggregate Diversity	0.411355	1
GINI index	0.964424	0
Exposure Distribution Entropy	3.812282	-
Average Recommendation Popularity	5716.980253	-



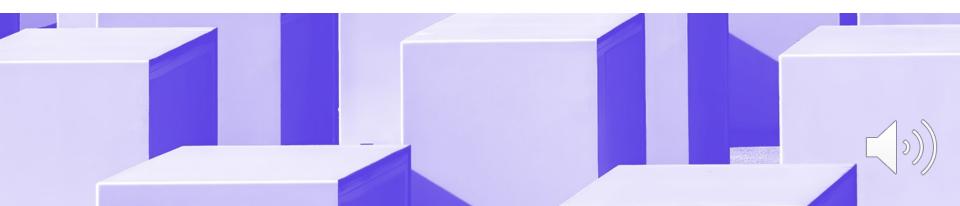
Exercise Notebooks

We have created exercise Notebooks for measuring Bias.



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

[1] Dash et al, 2021, When the Umpire is also a Player

[2] Deldjoo et al, 2022, A Survey of Research on Fair Recommender Systems

[3] Sun et al, 2019, Debiasing the Human-Recommender System Feedback Loop in Collaborative Filtering

[4] V. Tsintzou, E. Pitoura, P. Tsaparas, 2019, Bias disparity in recommendation systems

[5] M. Mansoury, B. Mobasher, R. Burke, M. Pechenizkiy, 2019, Bias disparity in collaborative recommendation

[6] Toshihiro Kamishima, Shotaro Akaho, Hideki Asoh, Jun Sakuma, 2018, Recommendation Independence

Sources

https://fairness-
tutorial.github.io/files/Tutorial on Fairness in Recommendation Slides.pdf
https://ir.library.louisville.edu/cgi/viewcontent.cgi?article=1440&context=faculty
<u> </u>
https://arxiv.org/pdf/2205.11127.pdf
https://arxiv.org/pdf/2005.01148.pdf
https://arxiv.org/pdf/2105.05779.pdf
Interpolitation of part 2 1001001 1 0 ipul