Adaptive Sythetic Generation of Indefinite Rankings

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1. Introduction

- Rankings systems are prevalent across a variety of domains, ranging from university rankings [3] to information retrieval [2].
- RBO is used to compare rankings where the domains may not be completely conjoint [4].
- Evaluating and comparing the effectiveness of RBO and its variants [1] may require synthetic rankings to be used.
- The synthetic ranking generation method used in [1] lacks flexibility.

2. Research Questions

The main research question that will be addressed in this research project is: **The current method to simulate synthetic rankings is not tailored to RBO's properties. How can we adapt this simulation taking inspiration from RBO?**

To help break this down further, four smaller sub-questions have been devised.

- What are the limitations of the current synthetic ranking generation method?
- How can the conjointness of the ranking domains be tuned?
- How can the overlap of items in rankings be adjusted given a probability function?
- How can the location and distribution of ties in a ranking be varied?

References

[1] Matteo Corsi and Julián Urbano.
The Treatment of Ties in Rank-Biased Overlap.
In *International ACM SIGIR Conference on Research and Development in Information Retrieval*, Washington, D. C., 2024.

[2] Lawrence Page, Sergey Brin, Rajeev Motwani, Terry Winograd, et al.
The pagerank citation ranking: Bringing order to the web.
1999.

[3] Tayyaba Rafique, Muhammad Usman Awan, Muhammad Shafiq, and Khalid Mahmood.
Exploring the role of ranking systems towards university performance improvement: A focus group-based study.
Heliyon, 9:e20904, 10 2023.

[4] W Webber, A Moffat, and J Zobel.
A similarity measure for indefinite rankings.
ACM Trans. Inf. Syst, 28, 2010.

3. Algorithm

- Generate two domains A and B, from which we draw items to place in S and L respectively. The conjointness of the two rankings is determined by the user input parameter `jaccard_similarity`.
- Add items $s \in A$ and $l \in B$ to S and L respectively. The choice of which subdomain to sample s and l from is determined by a Bernoulli random variable. If the outcome is 1, we increase the overlap. If the outcome is 0, we sample randomly. Repeat until all items in A and B have been ranked.
- Introduce ties into the simulation.
- Truncate rankings if required.

4. Example Rankings

Depth	S	L
1	i1	i1
2	i20	i20
3	i15	i18
4	a6	i15
5	i10	i4
6	i4	i11
7	i0	i0
8	i12	i21
9	i17	b21
10	i14	b22
11	i19	i12
12	i6	i5
13	i3	b26
14	i21	i6
15	a2	i9

Figure 1. Strong top-weighted overlap

Depth	S	L
1	i10	i17
2	a4	b26
3	i3	b12
4	i17	b6
5	i16	i12
6	a3	b0
7	i6	b9
8	i0	i0
9	a0	i20
10	i5	i8
11	i9	i6
12	i11	b21
13	i7	b15
14	i1	b23
15	i21	i13

Figure 2. Weaker top-weighted overlap

Depth	S	L
1	i7	i14
2	i14	i7
3	i11	i11
4	i0	i3
5	i8	i5
6	i2	i2
7	i3	i13
8	i5	i8
9	i13	i0
10	i12	i10
11	i6	i6
12	i4	i1
13	i10	i12
14	i1	i4
15	i9	i9

Figure 3. Uniformly distributed ties in both rankings

5. Results

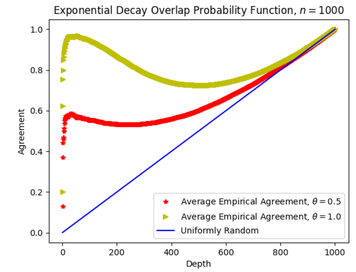

Figure 4. Rankings generated using an exponential decay overlap probability function with $\theta = 0.5$ vs $\theta = 1.0$

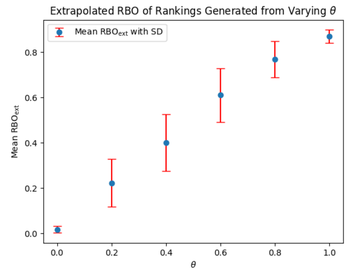

Figure 5. Average RBO_{EXT} scores for ranking pairs generated using an exponential probability function with varying θ

- By increasing the θ hyper-parameter value, we increase the degree of top-weightedness. As shown in Figure 5, the synthetic rankings are able to follow this property. The higher values for θ lead to, on average, larger RBO_{EXT} scores.

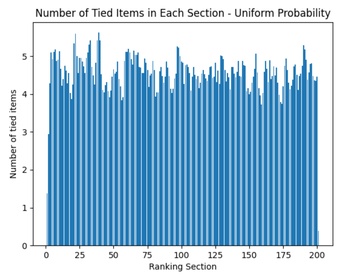

Figure 6. Spread of tied items across a ranking with 2000 items generated using a uniform distribution of ties

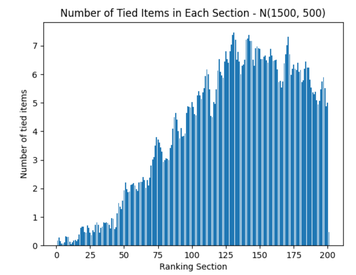

Figure 7. Spread of tied items across a ranking with 2000 items generated using a normal distribution of ties

- By varying the tie probability distribution, we observe differences in the spread of tied items across a ranking.

6. Conclusions

- This method takes inspiration from RBO by allowing conjointness, overlap and ties to be tuned.
- This method can be improved by varying the probability of choosing each case when adding new items. The analytical formula presented in the paper can also be further refined to better estimate the agreements given an overlap probability function f.