# Tailoring Synthetic Ranking Generation to RBO's Properties

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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. It also has the property of top-weightedness and can provide monotonically increasing/decreasing lower/upper bounds on the final value. [4]
- Evaluating the effectiveness of RBO (and its variants [1]) may require synthetic rankings to be used.

## 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, three smaller sub-questions have been devised.

- What is the current method to simulate rankings?
- What are the specific properties of RBO?
- If any, which (parametrisable) probability distributions define the properties of rankings?

## 3. Methodology

- review the source code used in [1] to simulate rankings.
- find a method to generate ranking domains given a Jaccard similarity value.
- identify a discrete probability distribution defining the probability of item agreement at a given depth, parametrised by some 'top-weightedness' hyperparameter $\theta$.
- introduce ties into the simulation
- evaluate simulation by calculating the RBO score of generated rankings.

## 4. Sample Simulated Rankings

| Rank | S | L |
|---|---|---|
| 1 | i15 | i4 |
| 2 | i58 | i47 |
| 3 | i51 | i39 |
| 4 | i13 | i20 |
| 5 | i40 | i35 |
| 6 | i23 | i23 |
| 7 | i49 | i22 |
| 8 | i28 | i58 |
| 9 | i7 | i31 |
| 10 | i56 | i46 |

Figure 1. $\theta = 0$

| Rank | S | L |
|---|---|---|
| 1 | i27 | i27 |
| 2 | i57 | i15 |
| 3 | i40 | i47 |
| 4 | i2 | i2 |
| 5 | i14 | i50 |
| 6 | i25 | i1 |
| 7 | i31 | i17 |
| 8 | i48 | i48 |
| 9 | i47 | i22 |
| 10 | i45 | i45 |

Figure 2. $\theta = \frac{1}{2}$

| Rank | S | L |
|---|---|---|
| 1 | i14 | i14 |
| 2 | i38 | i38 |
| 3 | i27 | i7 |
| 4 | i39 | i10 |
| 5 | i24 | i24 |
| 6 | i25 | i9 |
| 7 | i46 | i33 |
| 8 | i36 | i36 |
| 9 | i2 | i56 |
| 10 | i58 | i58 |

Figure 3. $\theta = 1$

## 5. Results

| $\theta$ | 0.0 | 0.2 | 0.4 | 0.6 | 0.8 | 1.0 |
|---|---|---|---|---|---|---|
| $RBO_{\text{ext}}$ | 0.097853 | 0.203534 | 0.311339 | 0.419992 | 0.530286 | 0.63779 |

Figure 4. Mean extrapolated RBO scores taken over 1000 ranking pair simulations. RBO evaluated from a prefix length of 60. The two rankings come from a fully-conjoint domain of size 200. $RBO_{\text{ext}}$ has been calculated using $p = 0.95$

## 6. Discussion

- we expect that RBO scores for a pair of rankings which has agreements at earlier depths will have high scores
- by increasing the $\theta$ hyper-parameter value, we increase the degree of top-weightedness. As shown in Figure 1, the synthetic rankings are able to follow this property. The higher values for $\theta$ lead to, on average, larger $RBO_{\text{ext}}$ scores.

## 7. Future Work (Week 5 - 9)

- refine probability function for top-weightedness
- introduce ties into the simulation
- identify some evaluation criteria to define the quality of the synthetic rankings generated

## 8. References

[1] Matteo Corsi and Julián Urbano.
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[2] Lawrence Page, Sergey Brin, Rajeev Motwani, Terry Winograd, et al.
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[3] Tayyaba Rafique, Muhammad Usman Awan, Muhammad Shafiq, and Khalid Mahmood.
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[4] W Webber, A Moffat, and J Zobel.
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