Diversity-Aware Reranking of Node2Vec-based Recommendations in Social Networks

Can diversity-aware reranking of node2vec-based link predictions reduce polarization after opinion dynamics, while preserving link prediction quality?

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1 WHY THIS MATTERS

- "People you might know" systems often recommend **similar users**.
- Connections between like minded people may lead to **echo chambers** and an increase in **polarization**.

2 BACKGROUND

- **Node2vec** represents each user as a vector learned from biased random walks through the network. Users with similar neighbourhoods or structural roles receive similar representations.
- **Opinion dynamics** models describe how opinions evolve through social influence. DeGroot averages neighbours' opinions, while BCM only allows influence between users whose opinions are sufficiently close.
- **LFR** is a synthetic graph generation method that results in power law distributions for degree and community sizes. We generate multiple graph configurations by varying μ, which controls community segregation, and η, which controls opinions consensus within a community.

3 APPROACH

Synthetic graph generated with LFR → Test split with positive and negative edges → Train node2vec embeddings → Score candidate links from test set → Diversity-aware reranking → Compute prediction quality → Add predicted links → Run opinion dynamics → Measure polarization

4 RERANKING METHODS

Opinion diversity

$$s_o(u,v) = \lambda \cdot s(u,v) + (1-\lambda) \cdot |o_u - o_v|$$

Rewards links between users with different opinions.

λ

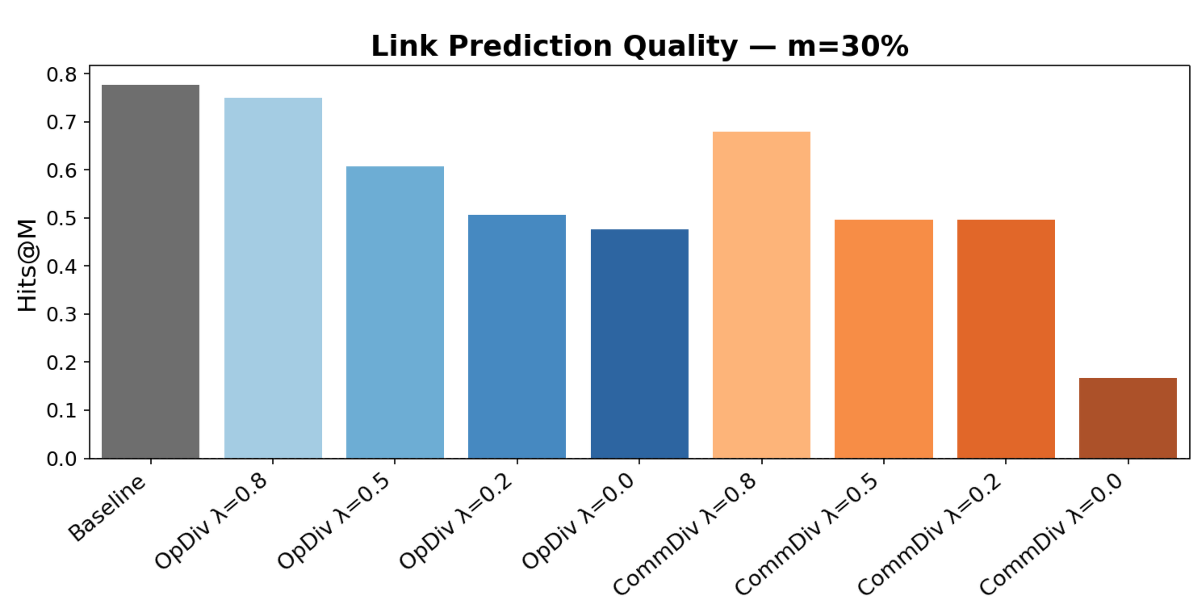
Controls the trade-off between the original node2vec score and diversity.

Community diversity

$$s_c(u,v) = \lambda \cdot s(u,v) + (1-\lambda) \cdot \mathbf{1}[c_u \neq c_v]$$

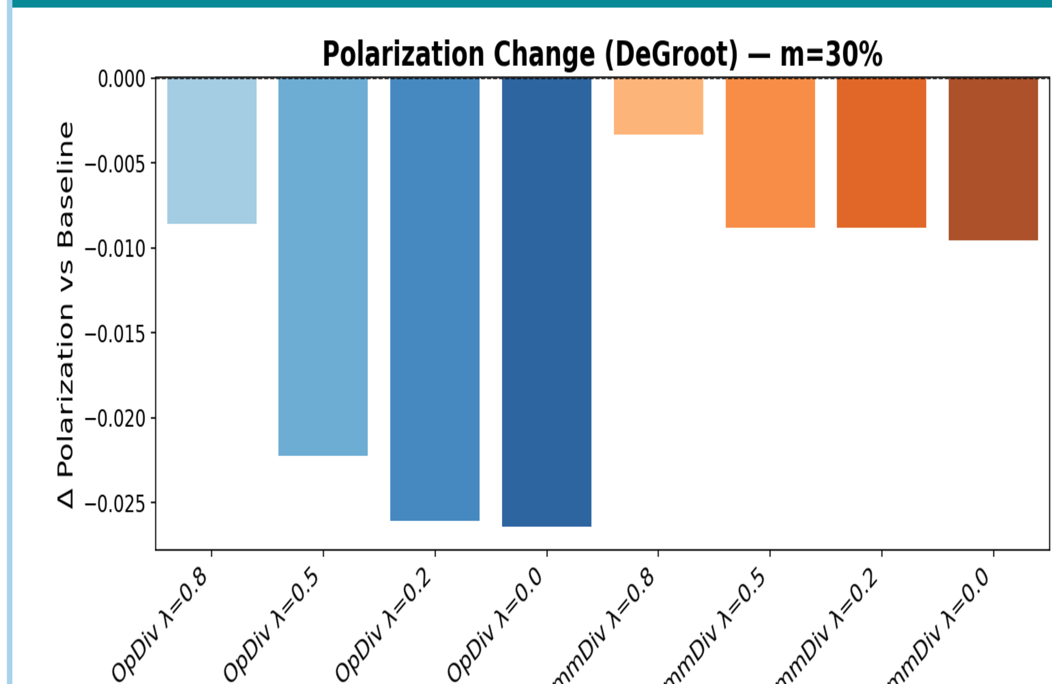
Rewards links connecting different communities.

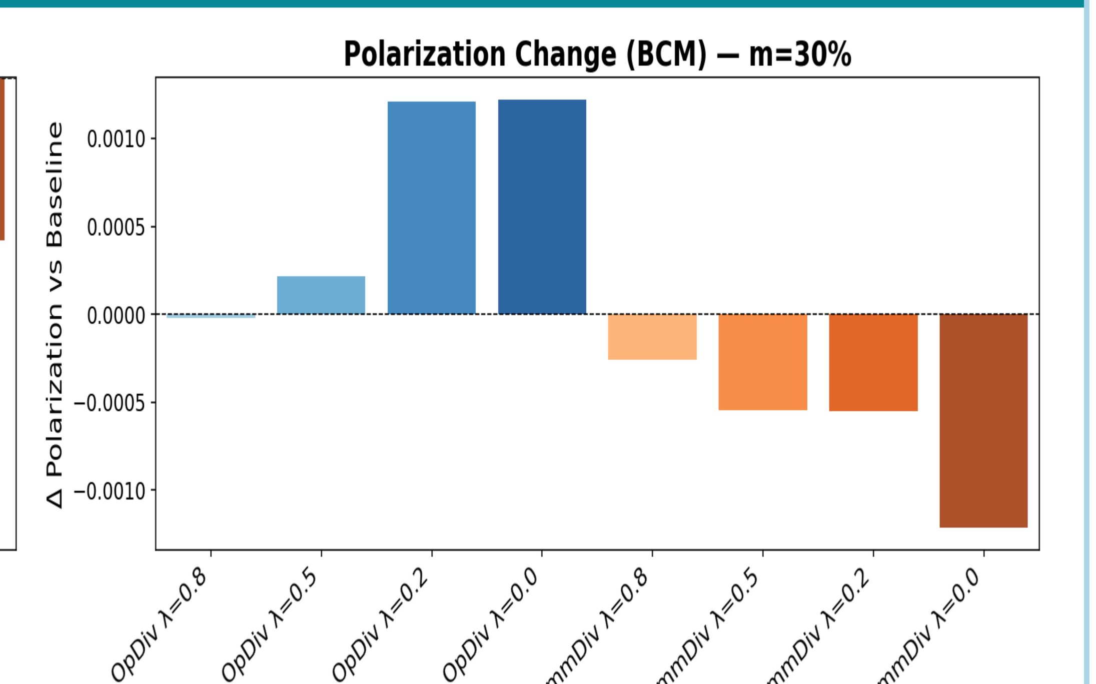
5 RQ1: How do diversity-aware reranking methods affect prediction quality?



Both reranking methods lower accuracy. Opinion diversity causes a smaller reduction than community diversity.

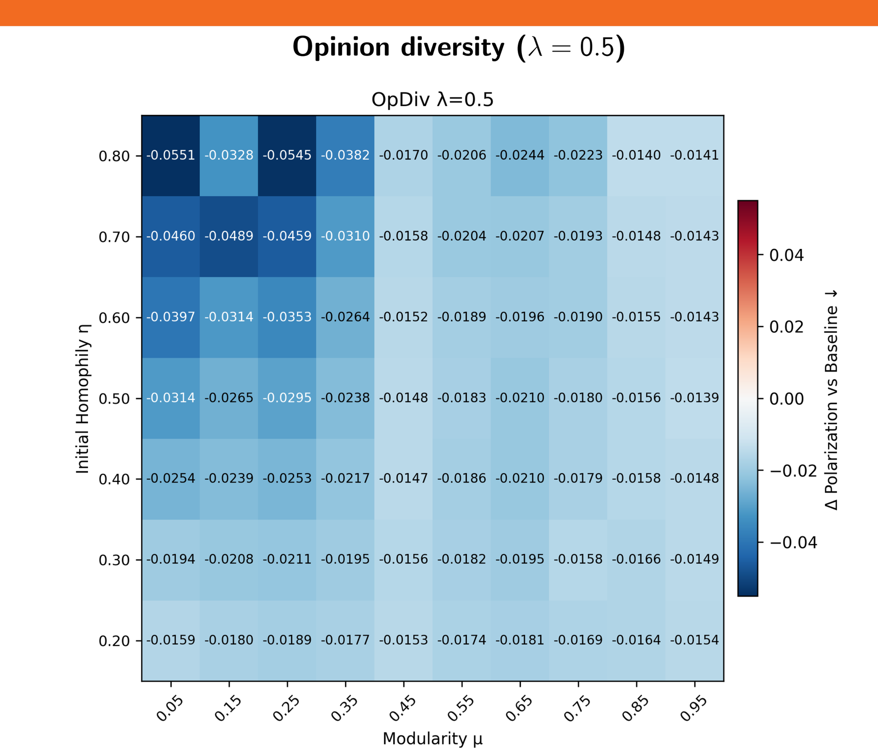
6 RQ2: How do reranking methods affect polarization after opinion dynamics?

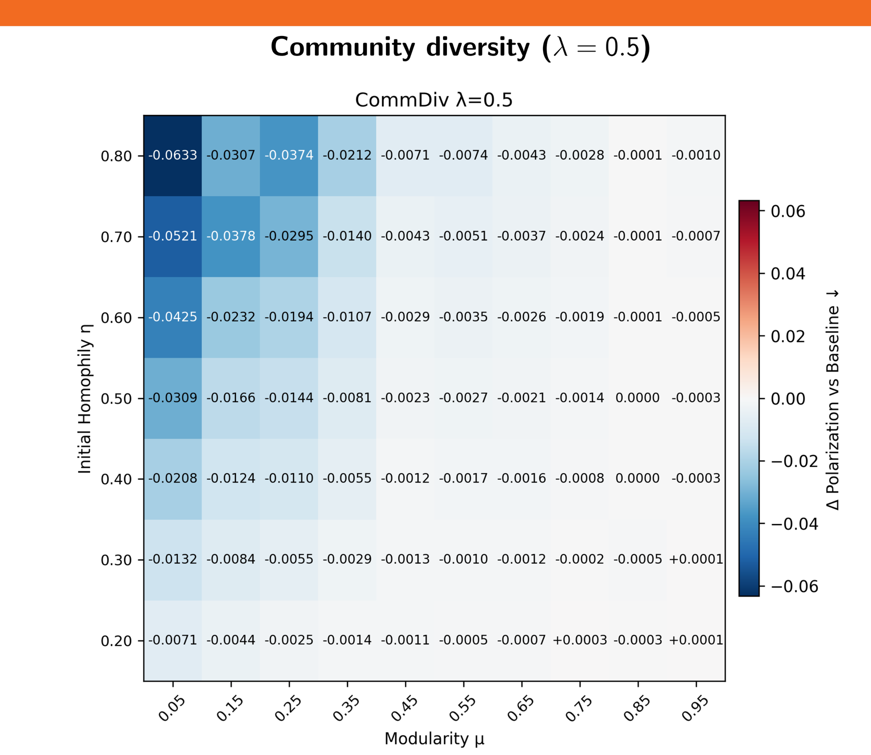




DeGroot: opinion diversity reduces polarization the most.
BCM: community diversity reduces polarization, while opinion diversity increases it.

7 RQ3: How does graph structure influence the polarization change?





Effects are strongest in already polarized graphs: low μ (well-separated communities) and high η (high opinion alignment).

8 LIMITATIONS & FUTURE WORK

Limitations

- Synthetic graphs are not a perfect proxy for real social networks.
- Prediction accuracy model is simplistic.
- The experiments use node2vec as the only underlying recommendation model.
- Conclusions depend on the assumptions of the chosen opinion dynamics models.
- The opinion dynamics models are run for only 10 iterations.

Future work

- Evaluate the reranking methods on real social network data.
- Model the probability that an user would accept a recommendation.
- Test reranking methos on other base recommender systems.
- Compare additional opinion dynamics models and polarization measures.
- Observe the longer-term network evolution of opinions.

9 REFERENCES

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