COMPLEX NETWORKS

2021

Recommender systems increase exposure diversity. Or do they ? A complex networks approach.

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Diversity, again ?

The role of diversity

- Individual: effect of percieved diversity on user engagement [2, 4]
- Collective: role of diversity in mitigating the effect of recsys in the apparition of filter bubbles [3]

The need for generalization

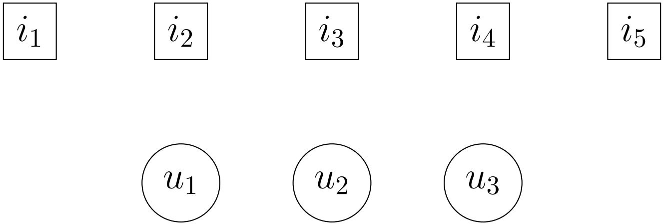
- Recommender systems: one author = one diversity measure [5]
- Need for comparison between models, with a common framework

Outline

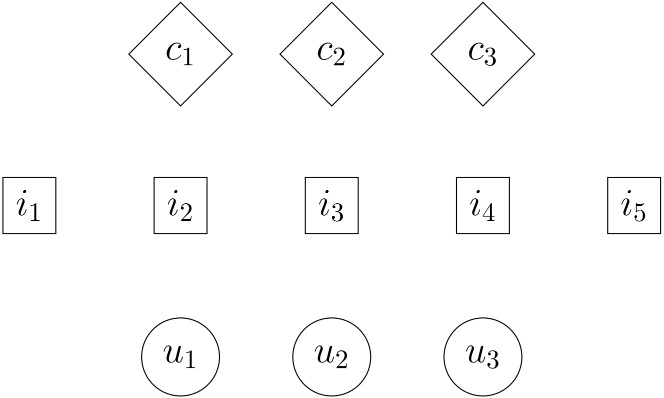
1. A general measure of diversity
    - Networks and recommender systems
    - The facets of diversity
    - Measuring diversity in HINs
2. An example with matrix factorization for music recommendation
    - Measuring the impact of recommendations
    - Balance versus variety
    - A user study
    - Conclusion

Networks and recommender systems

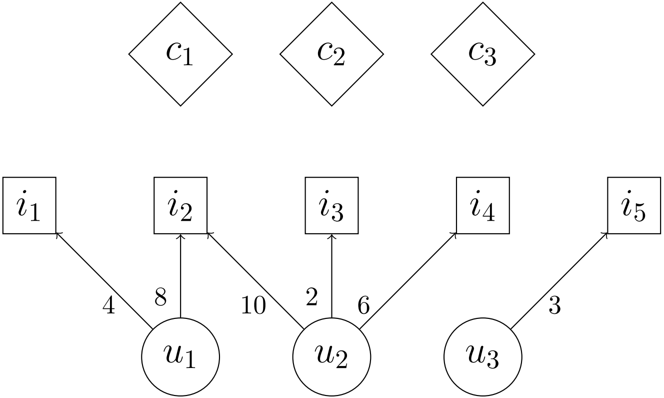
Networks and recommender systems



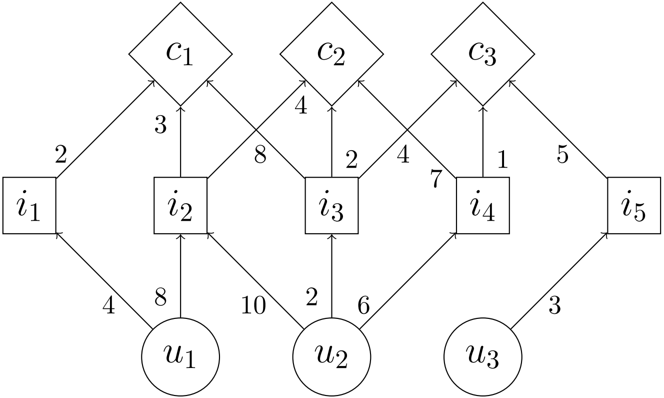
Networks and recommender systems



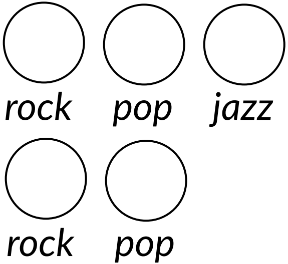
Networks and recommender systems



Networks and recommender systems



The facets of diversity



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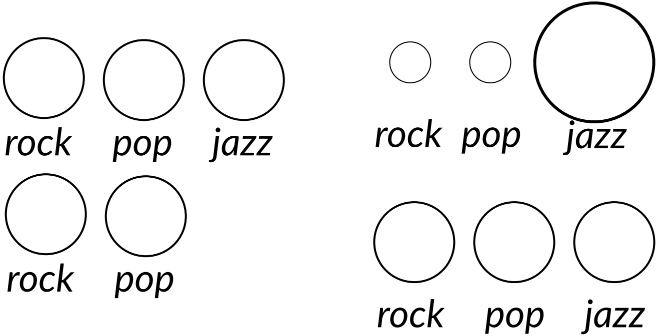

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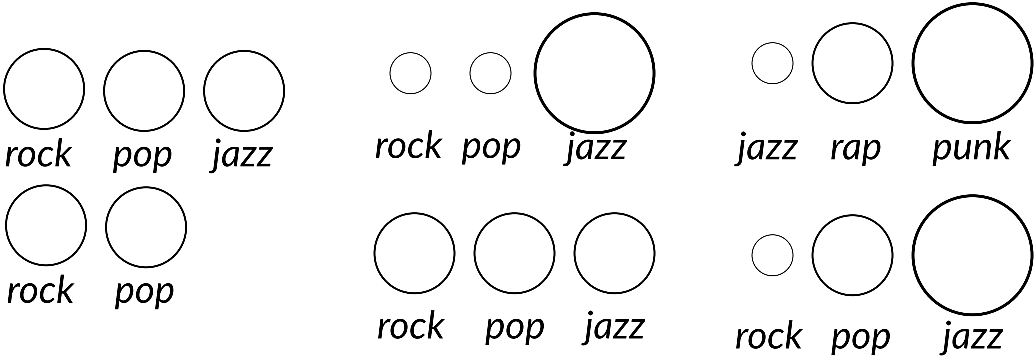
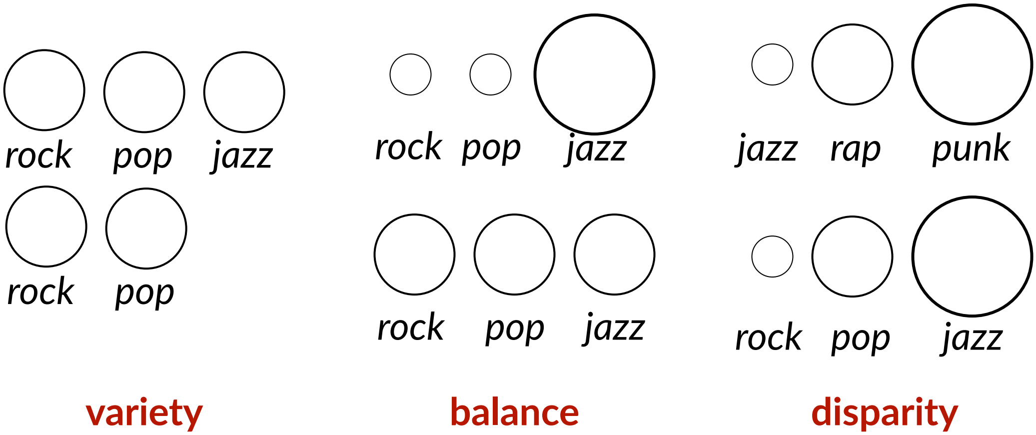
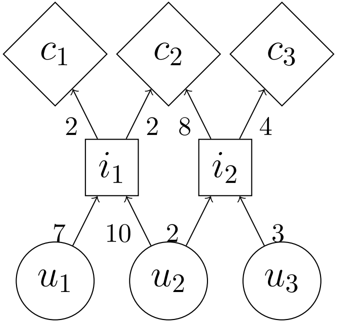


The facets of diversity

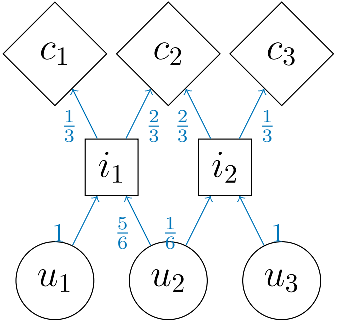


Measuring diversity in HINs



Measuring diversity in HINs

1. Normalize out weights



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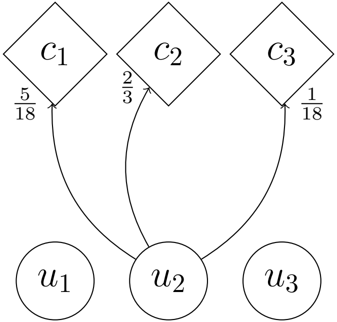
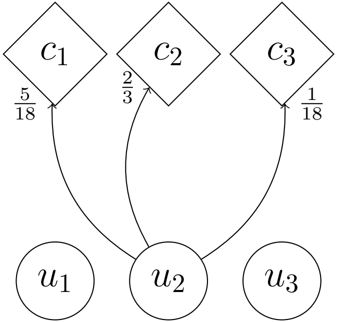


1. Normalize out weights
2. Compute transitions probabilities

$$p_{u_i \to c_j} = \sum_{i_k \in N(u) \cap N(c)} p_{u \to i_k} p_{i_k \to c}$$

Measuring diversity in HINs



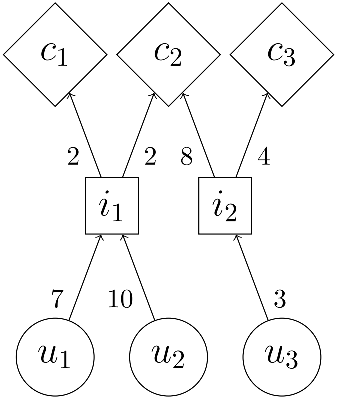
1. Normalize out weights
2. Compute transitions probabilities

$$p_{u_i \to c_j} = \sum_{i_k \in N(u) \cap N(c)} p_{u \to i_k} p_{i_k \to c}$$

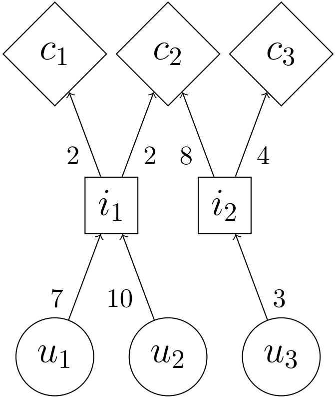
3. Compute true diversity of order α

$$D_\alpha(u_i) = \left(\sum_{j=1}^{k} p_{u_i \to c_j}^{\alpha} \right)^{\frac{1}{1-\alpha}}$$

Measuring the impact of recommendations



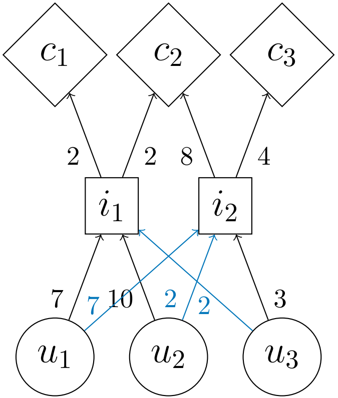
Measuring the impact of recommendations



1. Generate recommendations

$$x^*, y^* = \min_{x,y} \sum_{u,i} c_{ui} \left(r_{ui} - x_u^T y_i\right)^2 + \lambda \left(\|x\|_2^2 + \|y\|_2^2 \right)$$

Measuring the impact of recommendations



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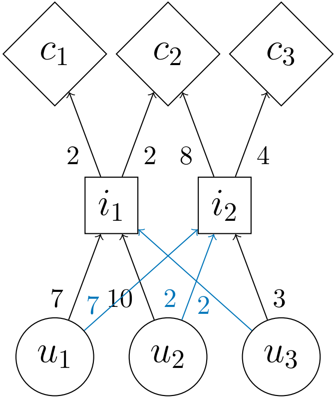
2. Insert recommendations

$$w(u,i) = \frac{2u_v}{k(k-1)} (k - \text{rank}(i,u))$$

Measuring the impact of recommendations



1. Generate recommendations

$$x^*,y^*=\min_{x,y}\sum_{u,i}c_{ui}\left(r_{ui}-x_u^Ty_i\right)^2 \\ +\lambda\left(\|x\|_2^2+\|y\|_2^2\right)$$

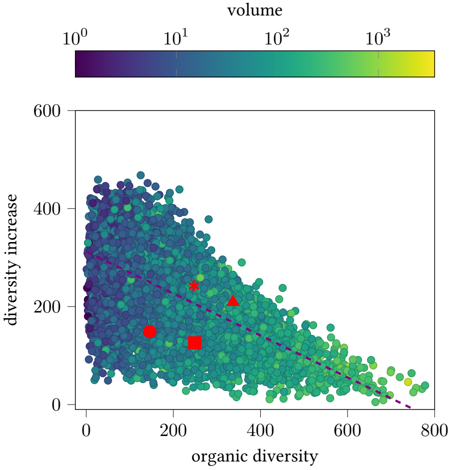
2. Insert recommendations

$$w(u,i)=\frac{2u_v}{k(k-1)}(k-\text{rank}(i,u))$$

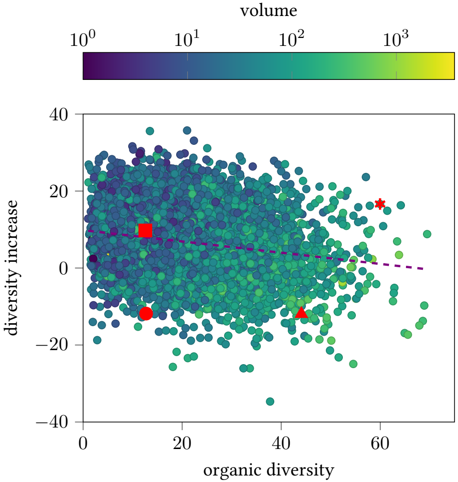
3. Compute the diversity increase

$$\Delta_\alpha\left(u_i\right)=D_\alpha(u_i^r)-D_\alpha(u_i)$$

Balance versus variety

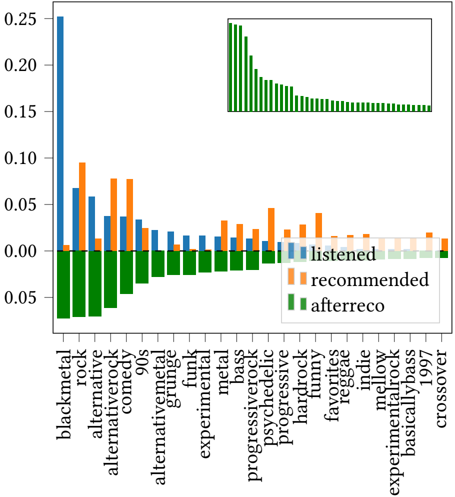


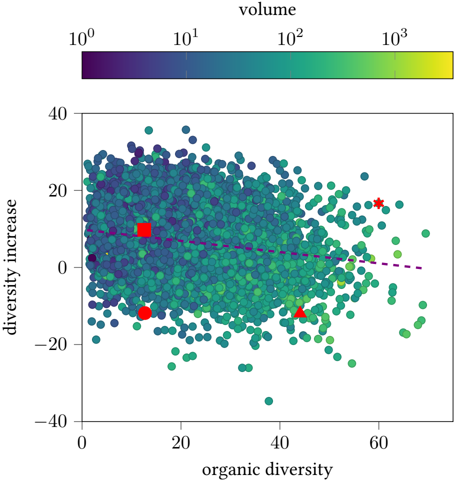
$\alpha = 0$



$\alpha = 2$

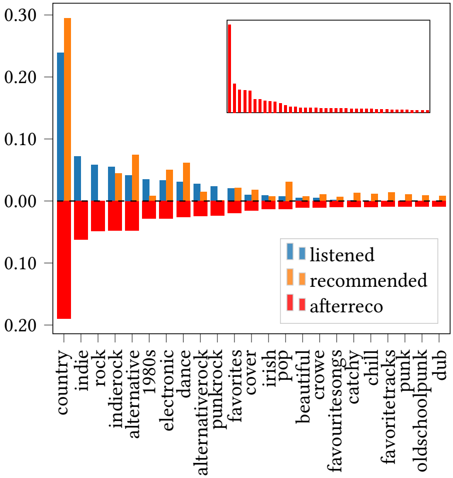
A user study– User *square*

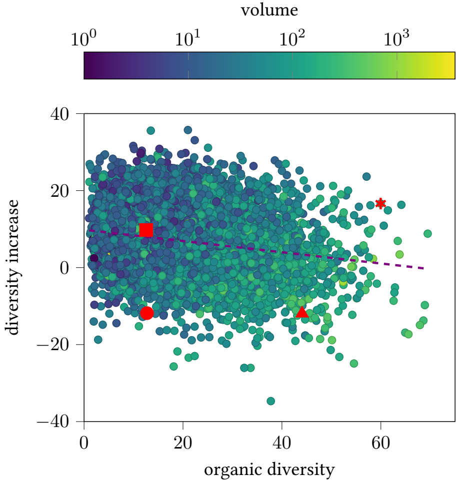




$\alpha = 2$

A user study– User *circle*





$\alpha = 2$

Conclusion

Take home messages

1. Introduced a mathematically sound diversity measure, suitable to a wide range of domains
2. Application on music recommender systems: matrix factorization seems to be unable to provide balanced recommendations

Code & slides at

`https://grodino.github.io/projects/recodiv/`

Thank you! *Questions ?*

To go further. Interested in

- the different aspects of diversity ? See [8].
- the diversity measure ? See [7].
- user models that capture observed diversity ? See [6].
- an online analysis of user musical diversity ? See [1]

Bibliography I

[1] Ashton Anderson et al. “Algorithmic Effects on the Diversity of Consumption on Spotify”. In: *Proceedings of The Web Conference 2020*. WWW ’20: The Web Conference 2020. Taipei Taiwan: ACM, Apr. 20, 2020, pp. 2155–2165.

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[7] Pedro Ramaciotti Morales et al. “Measuring Diversity in Heterogeneous Information Networks”. In: *Theoretical Computer Science* 859 (Mar. 6, 2021), pp. 80–115.

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[8] Andy Stirling. “A General Framework for Analysing Diversity in Science, Technology and Society”. In: *Journal of The Royal Society Interface* 4.15 (Aug. 22, 2007), pp. 707–719.