The role of Recommendation Algorithms in Opinion Polarization

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Summary

1. Recommendation algorithms, Eco Chambers and Filter Bubbles
2. Voter model with personalized information
3. Modelling collaborative filtering
4. Conclusions

Opinion Dynamics

Social systems show complex behaviors

- transitions from disorder to order
- scaling
- universality

Can we understand this with Statistical Physics?

Opinion Dynamics aims at explaining the formation of agreement among individuals:

- political parties
- cults and religions
- expansion of extremism

The New Information Age

We live in a digital society

- social networks
- streaming platforms
- e-commerce
- online information

Sources of information are central in Opinion Dynamics.

Online platforms influence the information we have access to!

Recommendation Algorithms

Online platforms contain tremendous amount of content

- Spotify (over 100 million tracks)
- Youtube (over 800 million videos)
- Facebook (over 2500 million users)

Recommendation algorithms guide us in this immense sea

- Selection of content/users that are close to our interests
- Only show us a very limited fraction of what is available

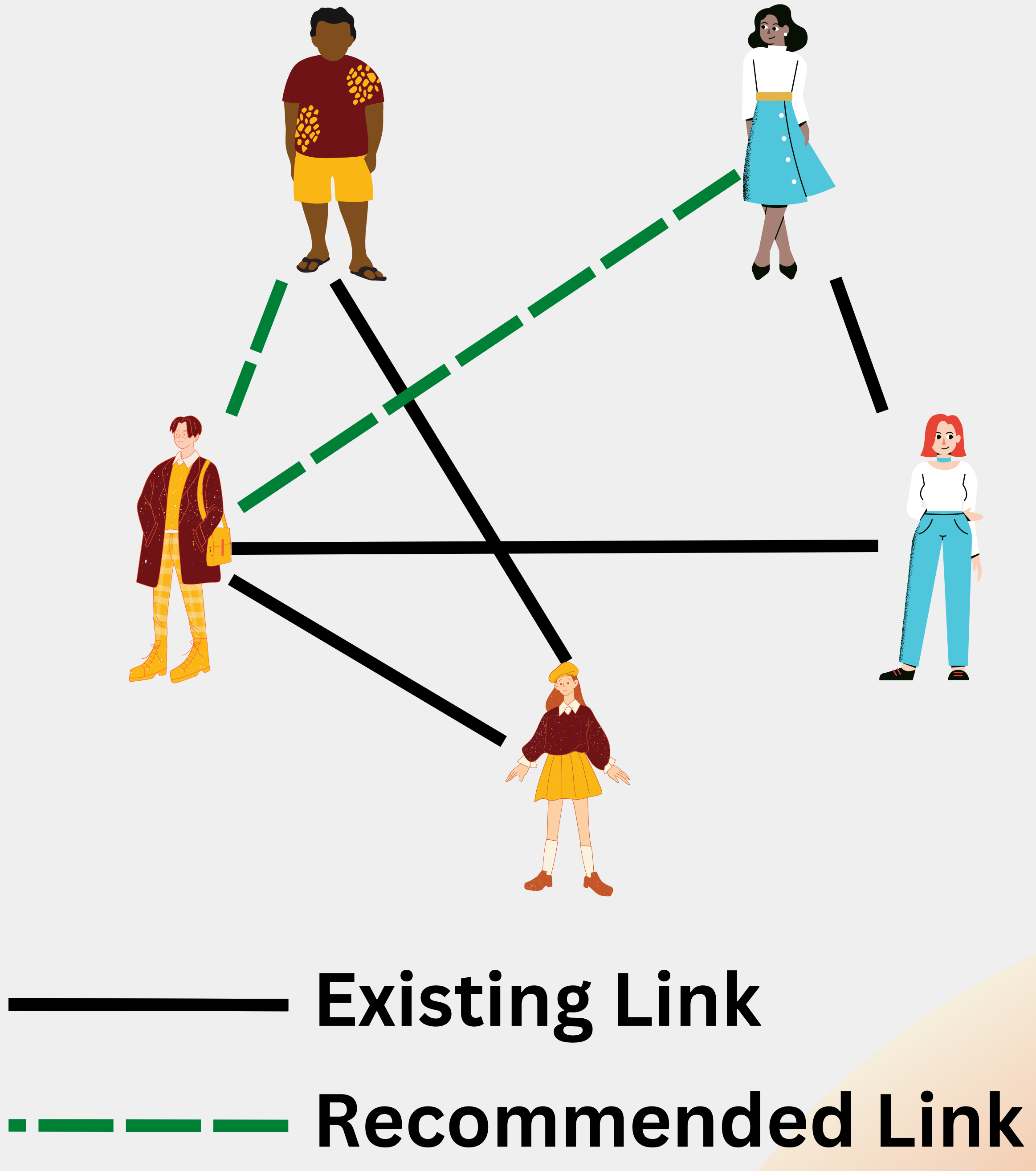
Link Recommendations

Link recommendations help us finding new friends on social networks

- "Suggested friends" on Facebook
- "People you may know" on Linkedin

Possible mechanisms:

- **Structure based.** The friend of my friend is a potential friend
- **Opinion based.** A person with similar interest is a potential friend

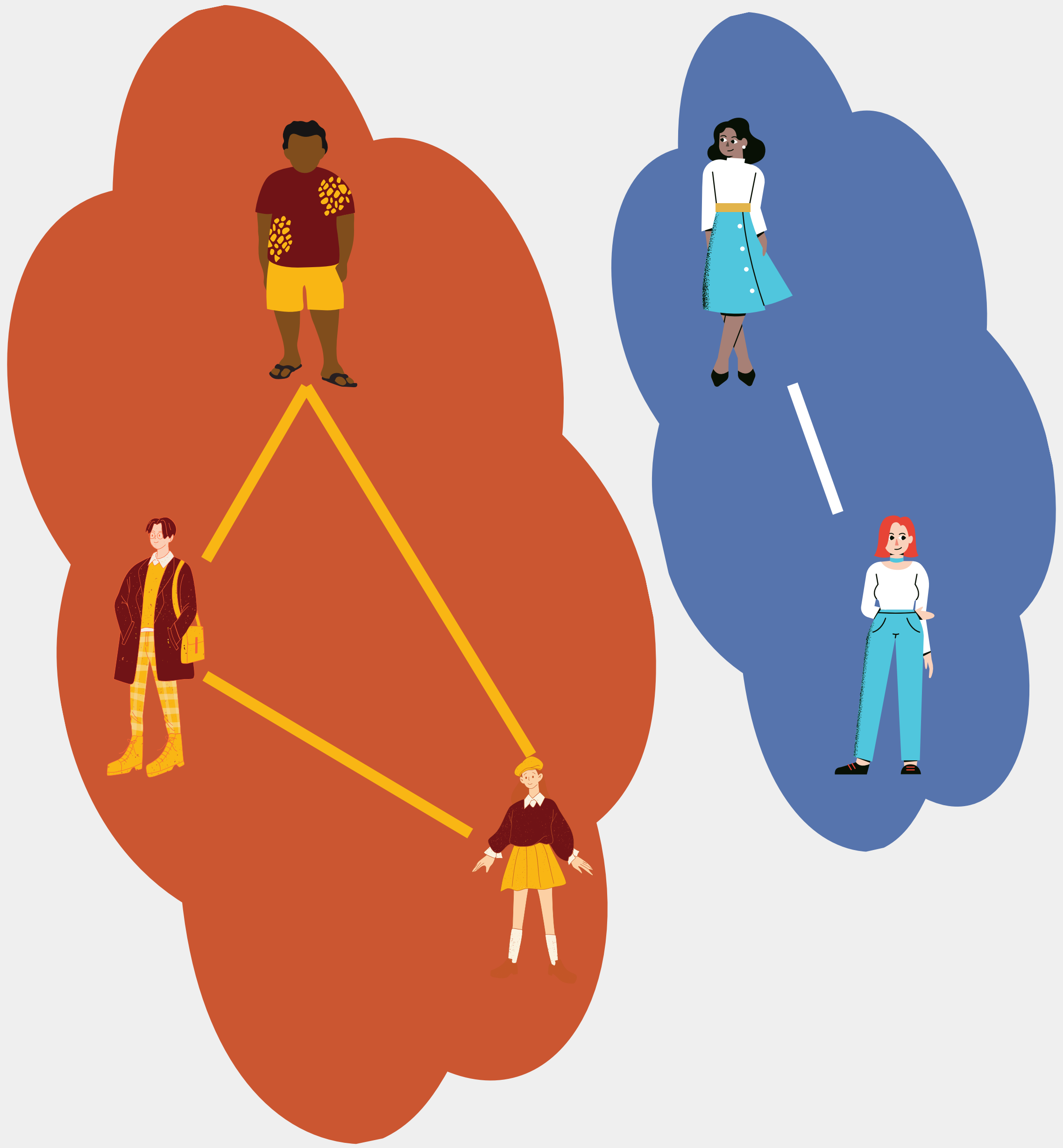


Eco Chambers

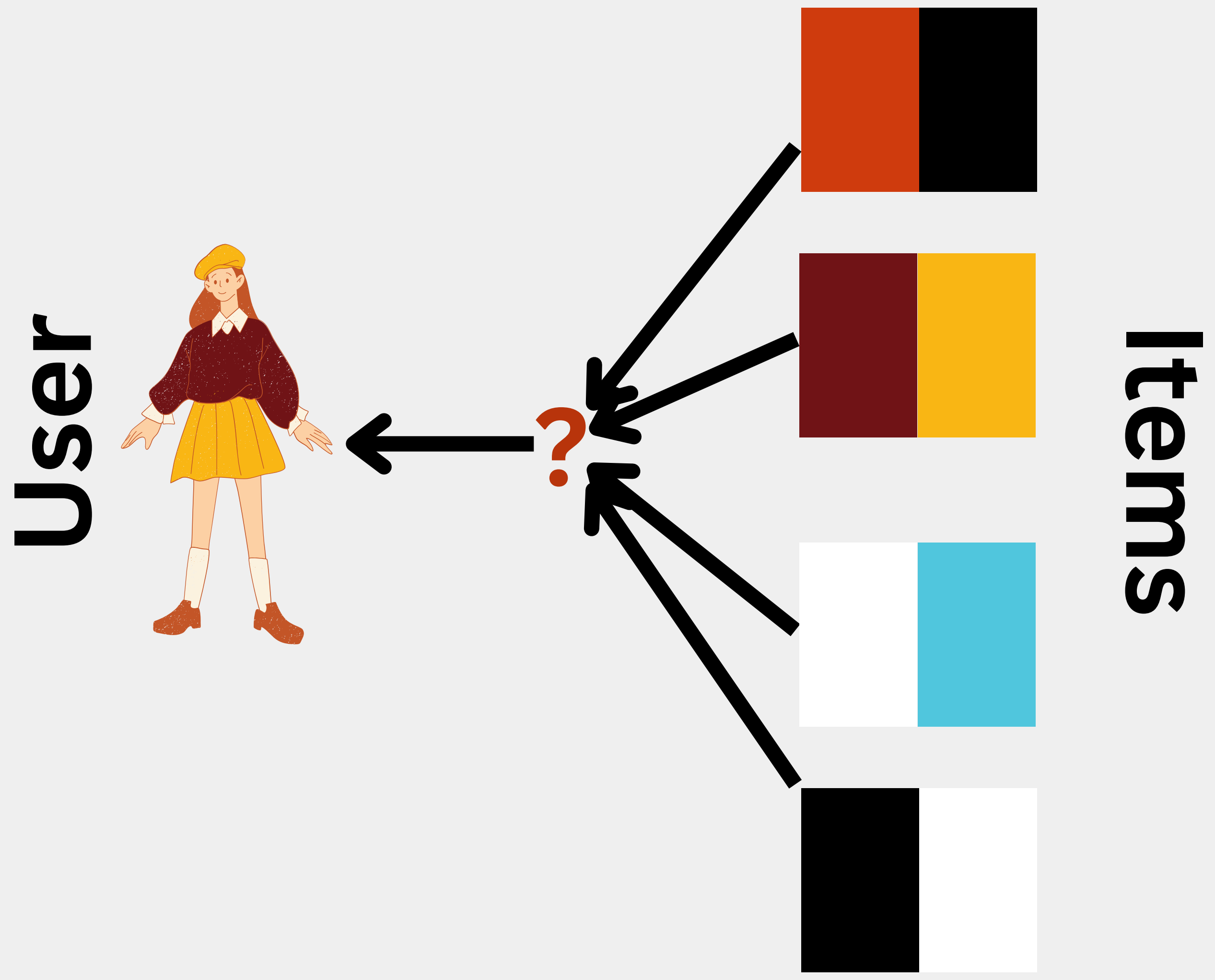
By suggesting friends, link recommendations make us interact with people which are similar to us

Echo Chamber Effect:

each individual is connected mainly to other individuals sharing her same ideas and believes



Content Recommendations



Content recommendations help us finding new items on online platforms

- "Suggested for you" posts on Facebook
- "Items you may like" on Amazon

Possible mechanisms:

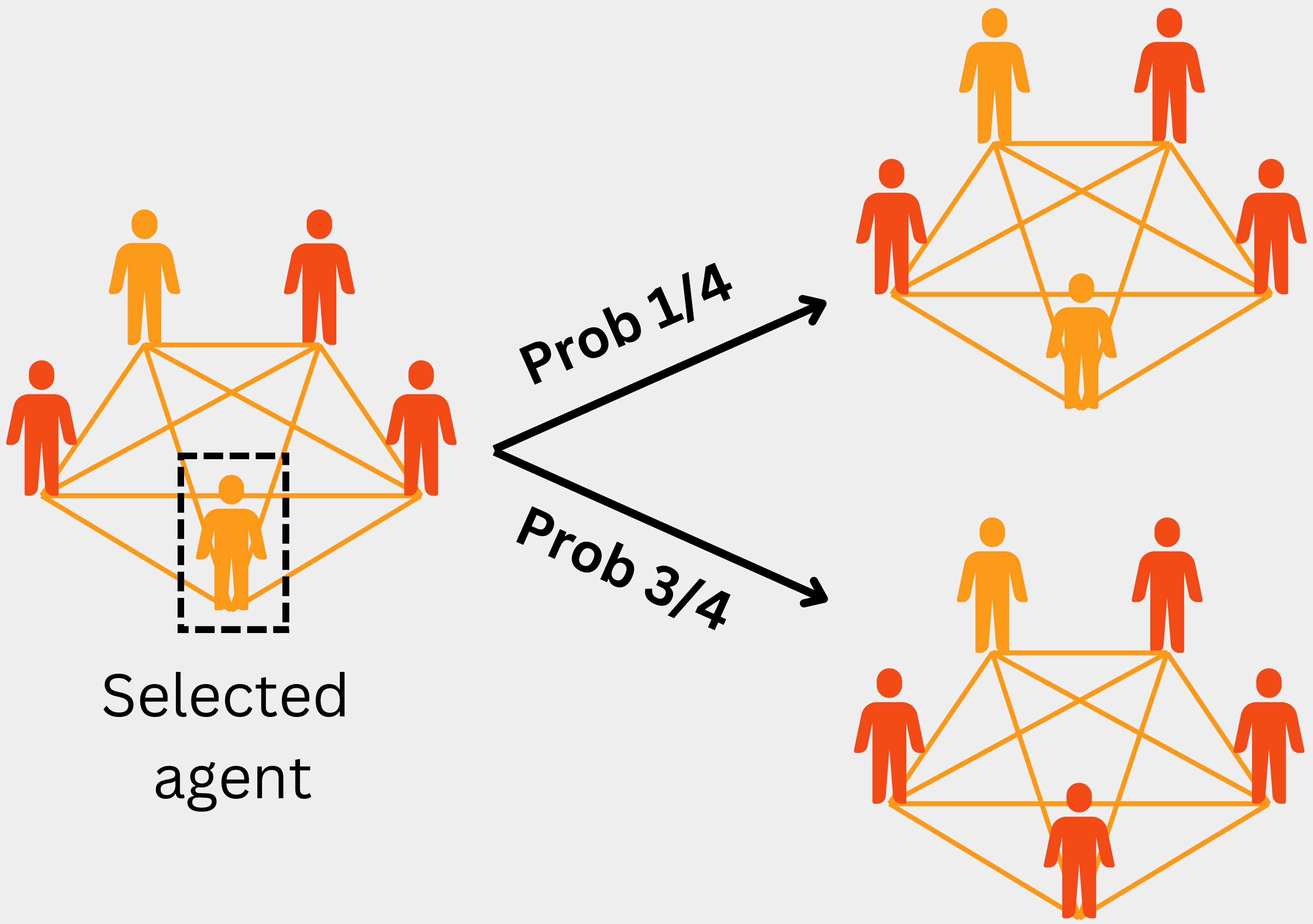
- **Content based.** Looks at similarity between the contents.
- **Social based.** Uses social network to recommend items
- **Collaborative based.** Uses the behavior of other users

Filter Bubbles

Content recommendations make us look at information that is in line with our ideas

Filter Bubble Effect:
each individual is exposed to personalized content that confirms its believes

Voter Model...



Model of opinion dynamics:

- Binary opinions $s_i = \pm 1$
- Ferromagnetic interaction

Agents copy the opinion of random neighbors

We only consider the fully connected case

...with Personalized Information

Each agent is exposed to a source of personalized information e_i

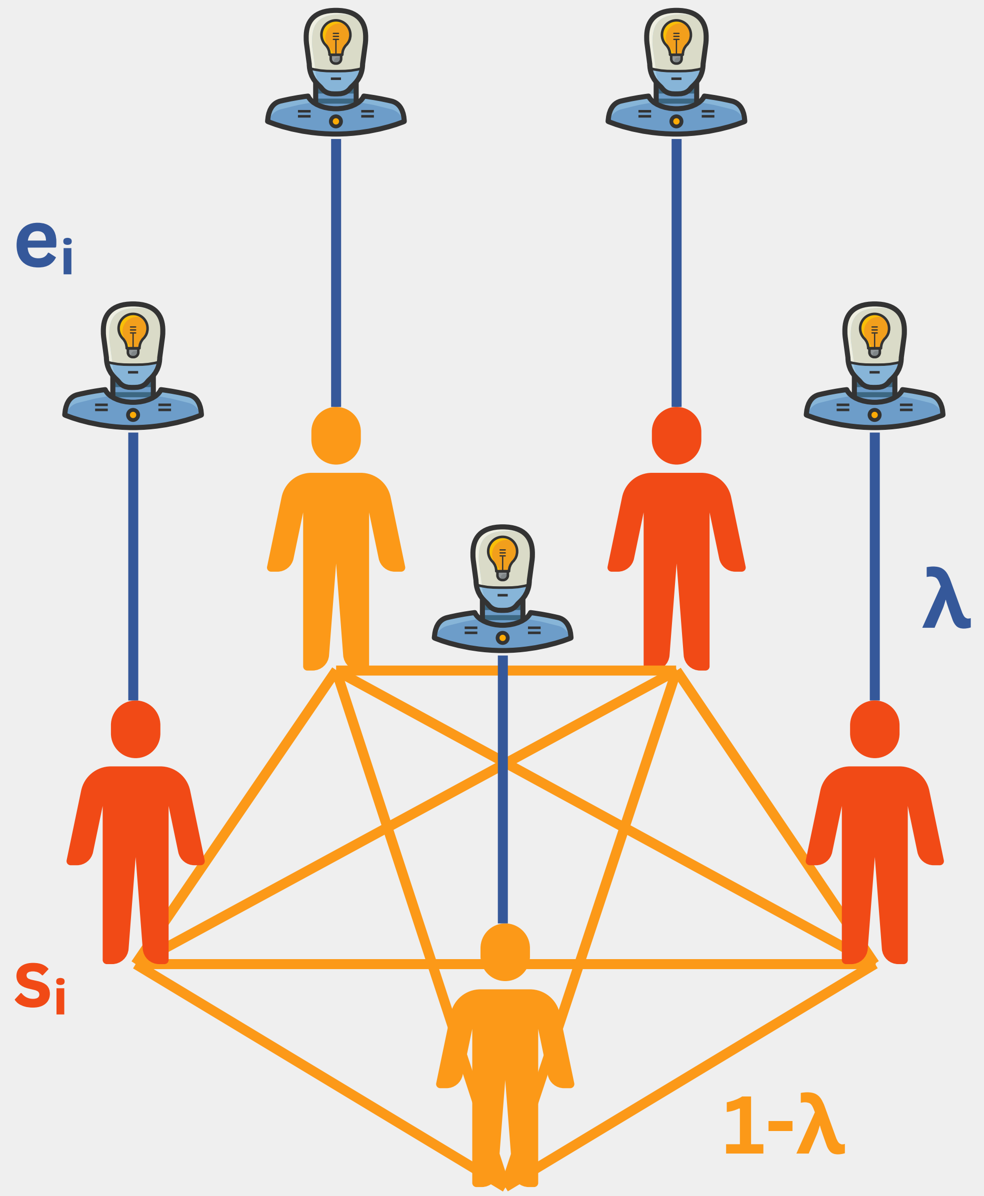
$1 - \lambda$ Copy the opinion of random agent

λ Follow the recommendation

Personalized information reinforces agents' most common opinion

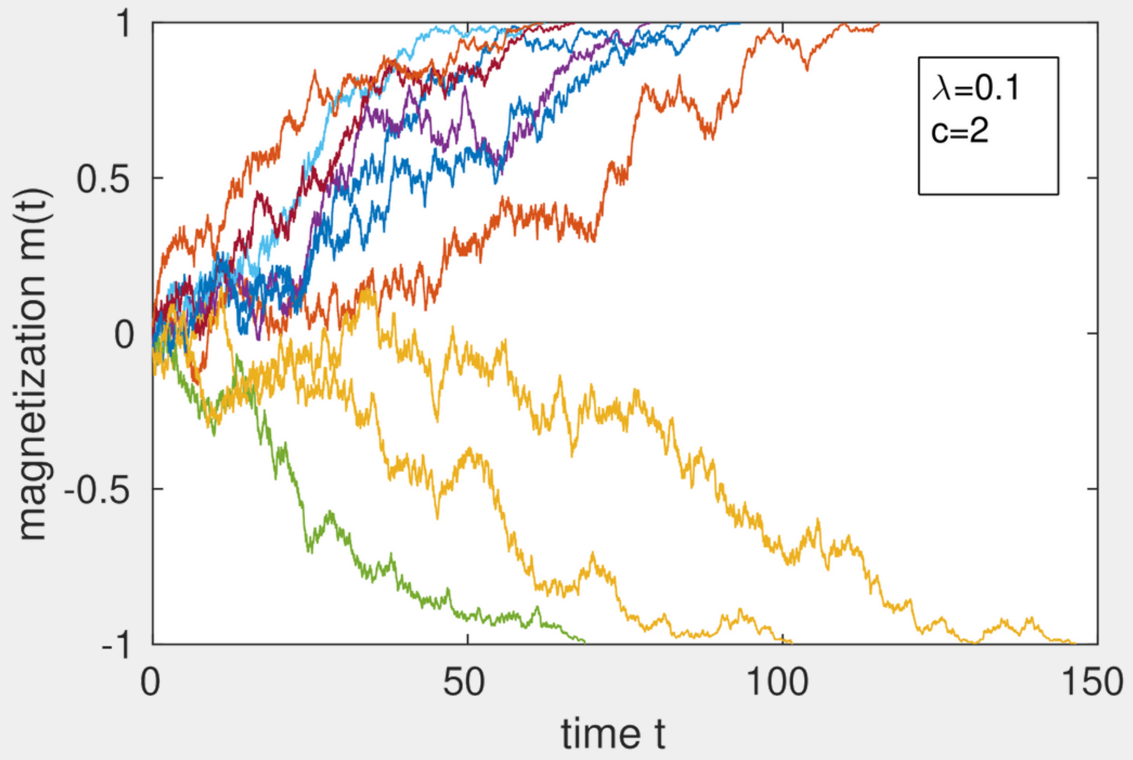
$$n_i = \text{positive clicks} \ - \ \text{negative clicks}$$

$$P[e_i(t) = 1] = P[n_i] = \frac{c^{n_i}}{1 + c^{n_i}}$$

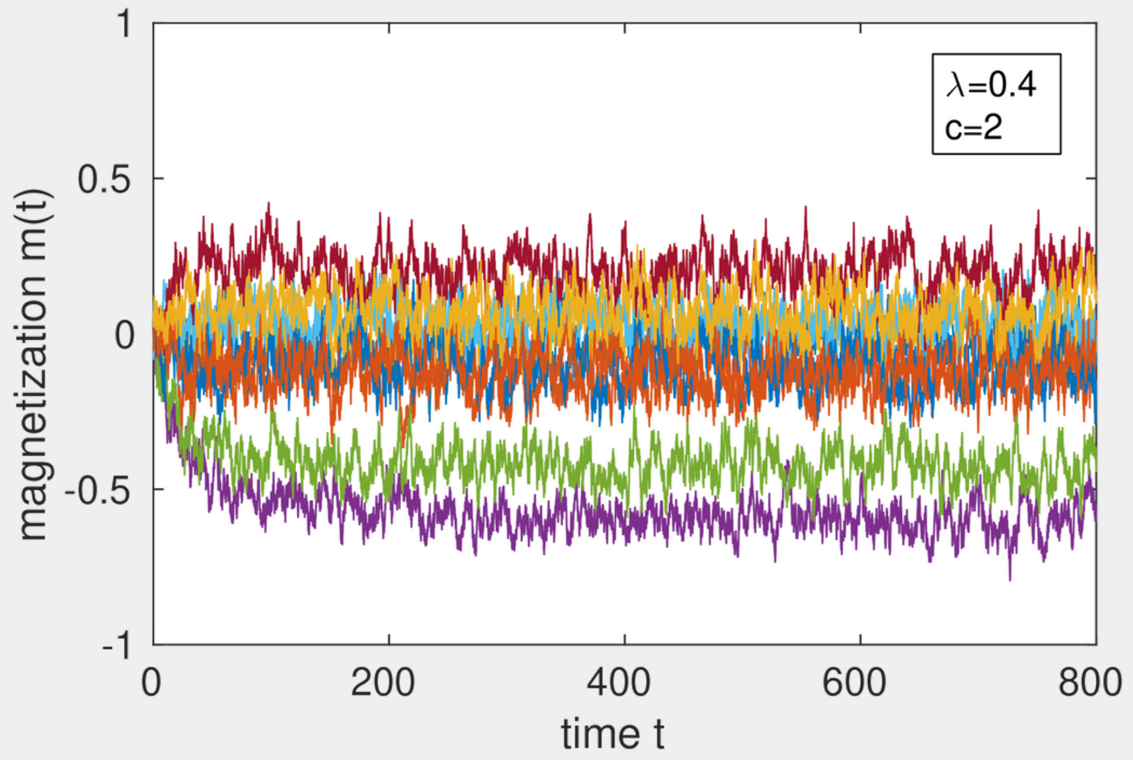


Fragmented states

We look at the magnetization $m = \frac{1}{N}\sum_i s_i$

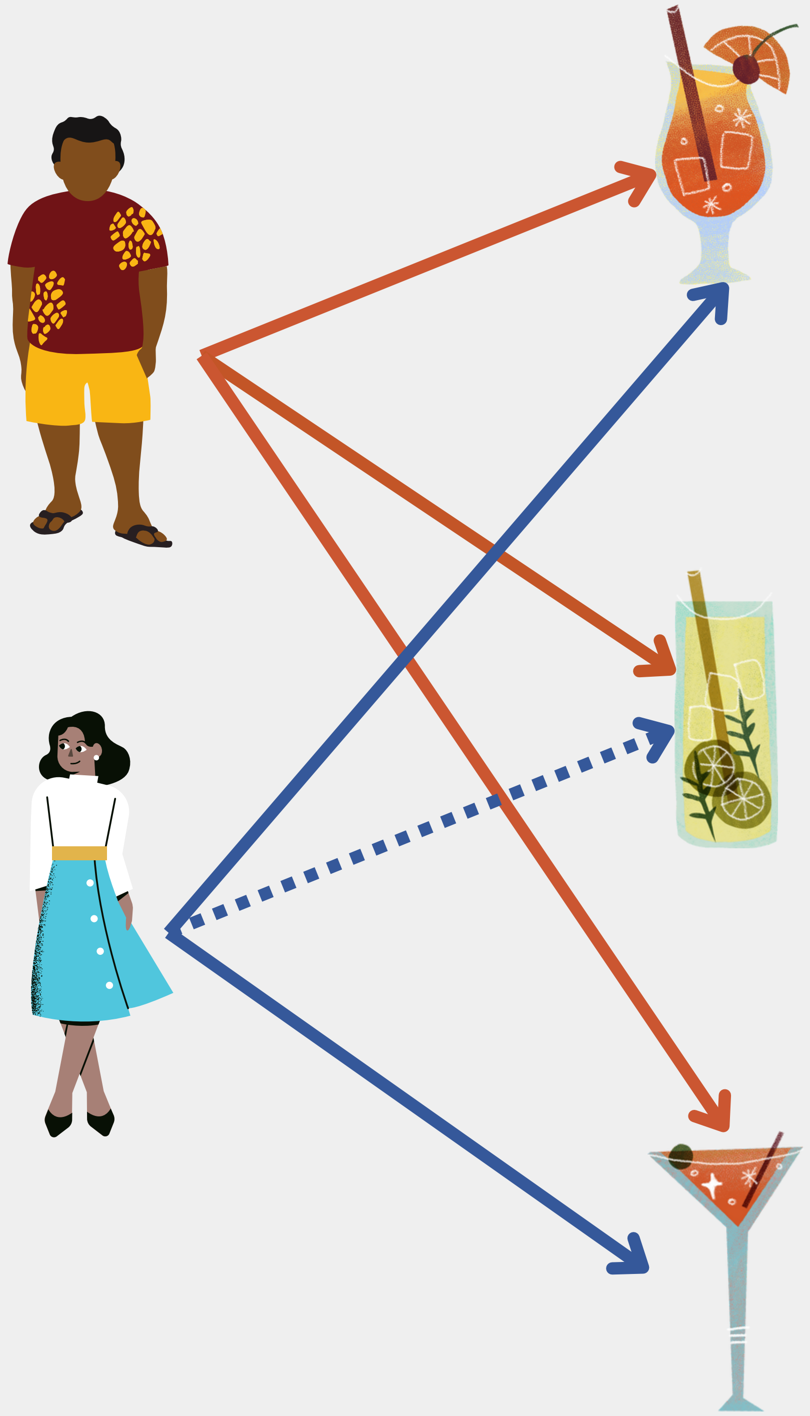


Stronger personalized information →



Polarized states with |m|<1 are stable if $|m| < m_c = \frac{\lambda}{1-\lambda}$

Collaborative Filtering in Short



Techniques for providing recommendations based on similarities

- user-user
- item-item (Amazon)
- matrix factorization (Netflix)

Consider the bipartite network of users and opinions/items

Modelling the User-User Collaborative Filtering

Users similarity

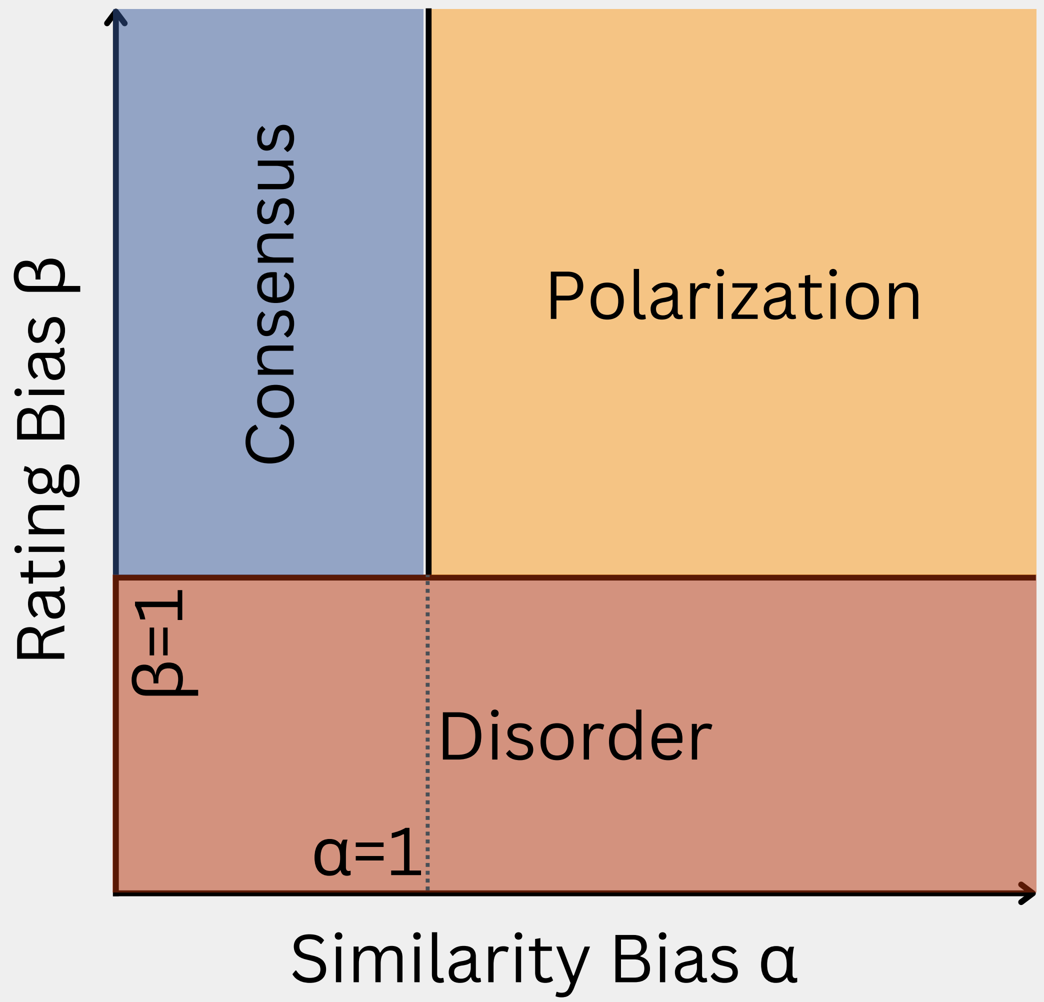
$$s_{ij} = \frac{\sum_a^M n_{ia} n_{ja}}{\sqrt{\sum_a^M n_{ia}^2} \sqrt{\sum_a^M n_{ja}^2}}$$

Clicking Probability

$$R_{ia}(t) = \frac{1}{N} \sum_j^N \frac{s_{ij}^{\alpha}(t)}{\sum_k^N s_{ik}^{\alpha}(t)} \frac{n_{ja}^{\beta}(t)}{\sum_b^M n_{jb}^{\beta}(t)}$$

1. N users and M items
2. Higher probability of choosing opinions frequently chosen by similar users
3. Two parameters:
   -similarity bias α
   -rating bias β

Phase Diagram



For large N, M three distinct phases emerge:

- Disorder
- Consensus
- Polarization

All phases present problems

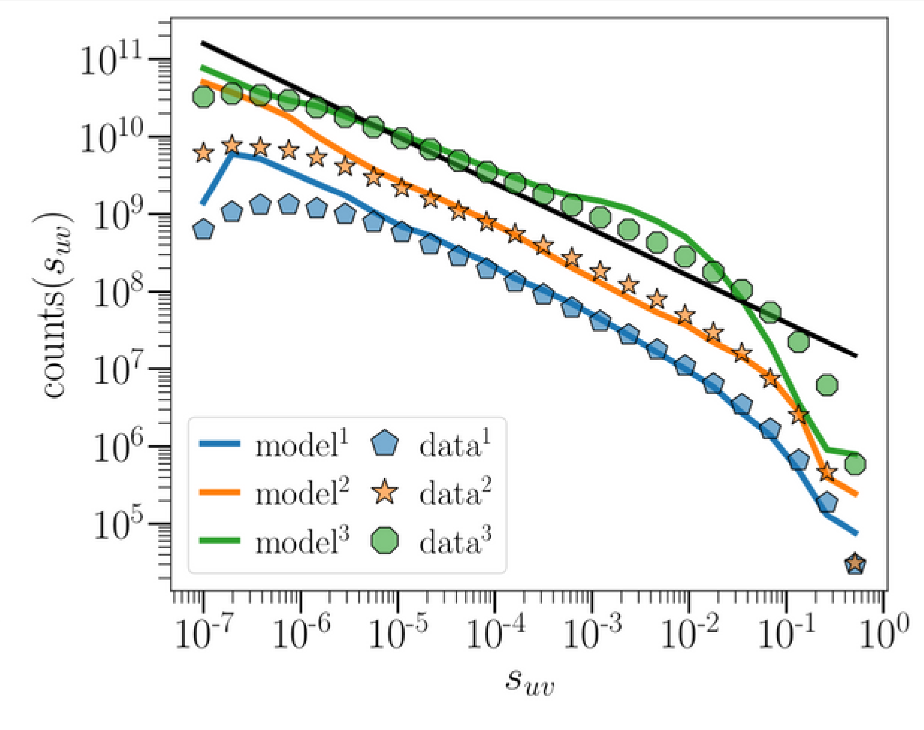
- no personalization (D and C)
- filter bubble (P)

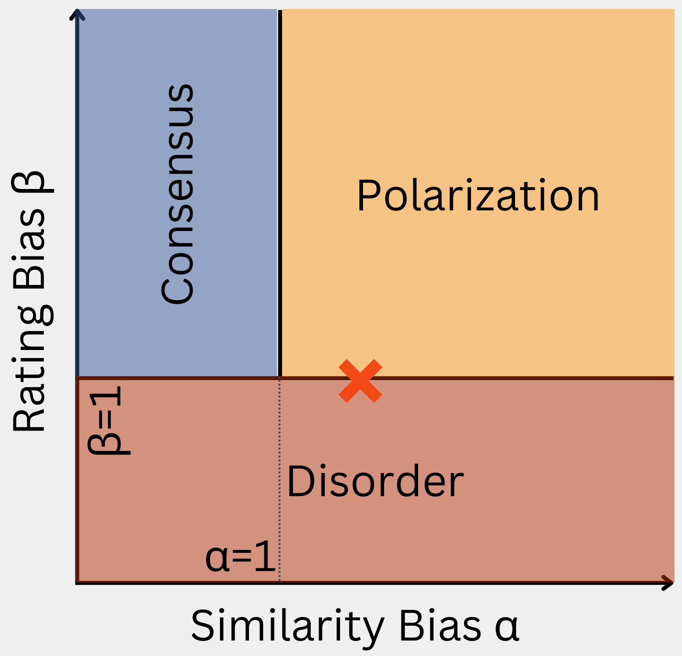
On the critical line $\beta=1$ we observe an intermediate behavior with only partial polarization.

Music Recommendations

We can use our model to fit the behavior of users. We look at the online music platform last.fm

- 1000/2000/5000 users
- 500/1000 artists
- the model well reproduces the similarity among users
- the parameters are β=1 and α≈2





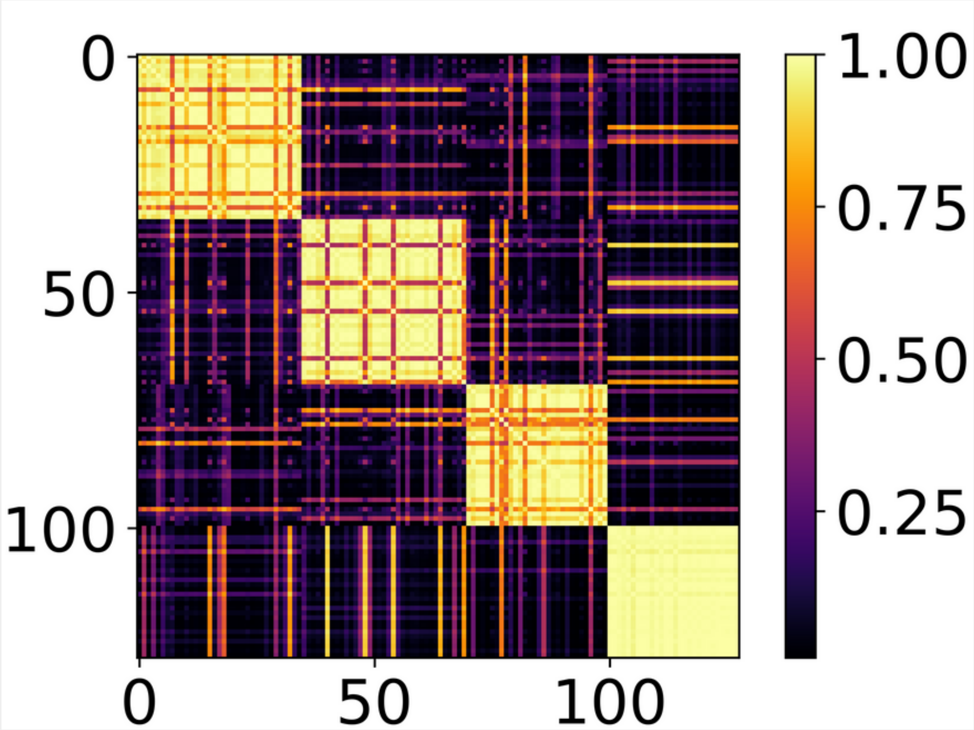
Matrix Factorization

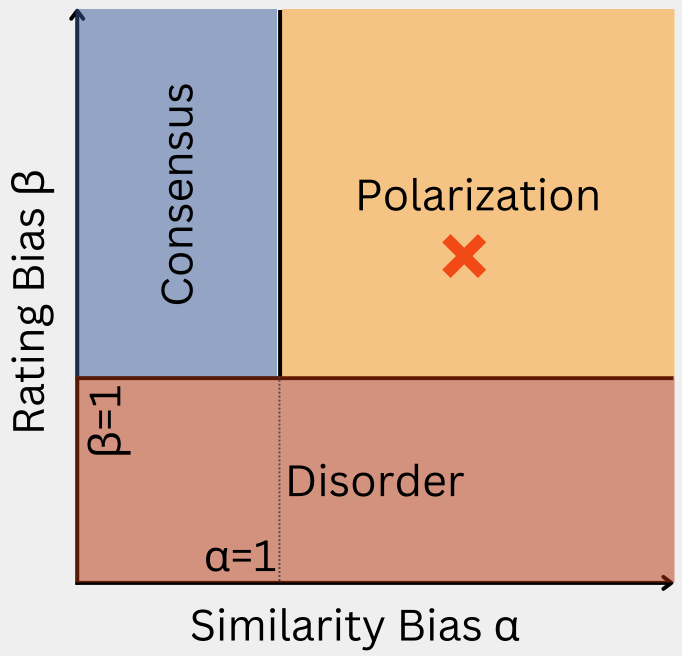
Matrix factorization

- more sophisticated than user-users collaborative filtering
- leverages on dimensionality reduction

We observe that matrix factorization

- induces opinion polarization
- is equivalent to the user-user collaborative filtering with large α and β





Conclusions

- Statistical Physics can help in understanding the potential effects of recommendation algorithms
- Recommendation algorithms enhance opinion polarization and the formation of filter bubbles
- We can tune the parameter of the algorithms to mitigate their downsides

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End

Thank you

Do you have any questions?