Experiential Preference Model: “The friend of my friend is ?”

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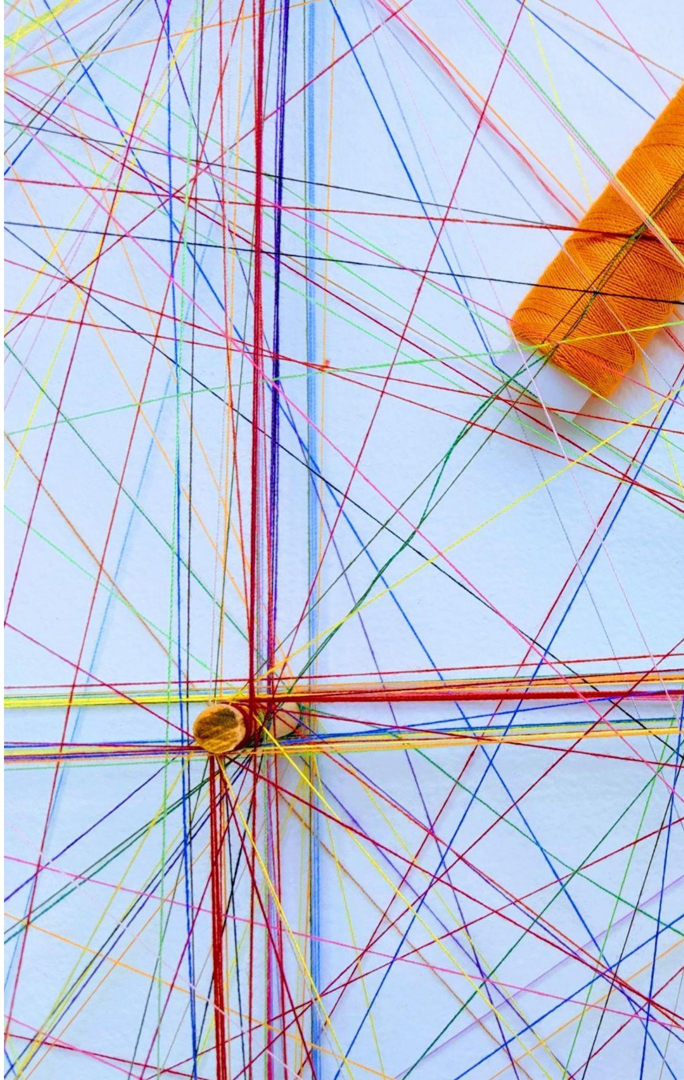
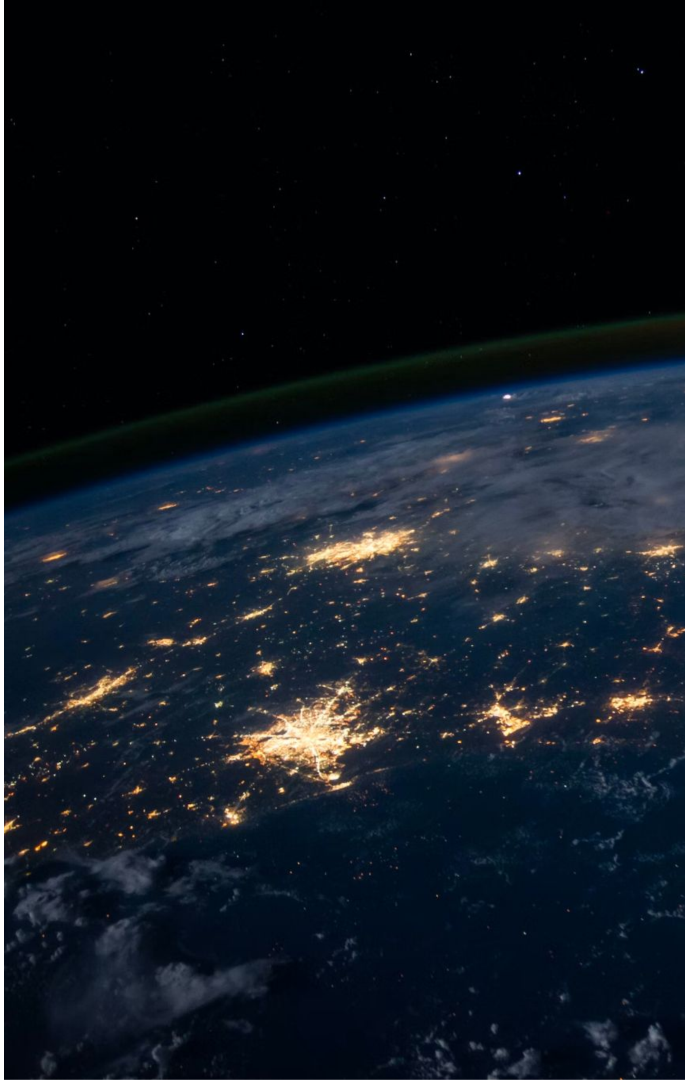
Content

1. **Motivation & Relevance**
2. Our Model
3. Results



Motivation & Relevance (1/2)

- Understanding social influence
- Understanding: Consensus & Polarization, Extremism
- Policy and Decision making: outcomes of political campaigns, marketing strategies, or public policy initiatives
- Simulation and Prediction



Motivation & Relevance (2/2)

- Trends on social media
- Borrows knowledge from psychology: Cognitive Dissonance
  - as well as economics, physics, and computer science
  - holistic and interdisciplinary insights into human behavior

- Examples:
  - Political vote
  - Opinions
  - Cultural features
  - Marketing, trends

Related Work: The Deffuant Model (1/6)

- Voter model (binary) -> Continuous models
- Guillaume Deffuant et al. early 2000s:
  - **Bounded confidence**: Individuals only influenced by opinions within a certain range (confidence interval)
  - **Pairwise interaction**: Random meetings between individuals leading to opinion adjustments
  - Interaction rule: If the difference in opinion ≤ confidence bound, opinions converge
  - Opinion update: Average of two opinions within the confidence bound

Related Work: The Deffuant Model (2/6)

- Comparison to other models
  - Hegselmann-Krause model: Continuous opinions with group influence
  - Axelrod: Multiple variable per agent possible
  - Strengths of Deffuant: Simplicity, adaptability to various scenarios

- Limitations:
  - Assumes rational averaging
  - Overlooks external factors like media
  - Random interactions
  - Overlooks the possibility of gradual or delayed opinion change over time.
  -

Related Work: The Deffuant Model (3/6)

x, x’: Opinion

k: Kernel function

θ : tolerance threshold

μ : interaction intensity

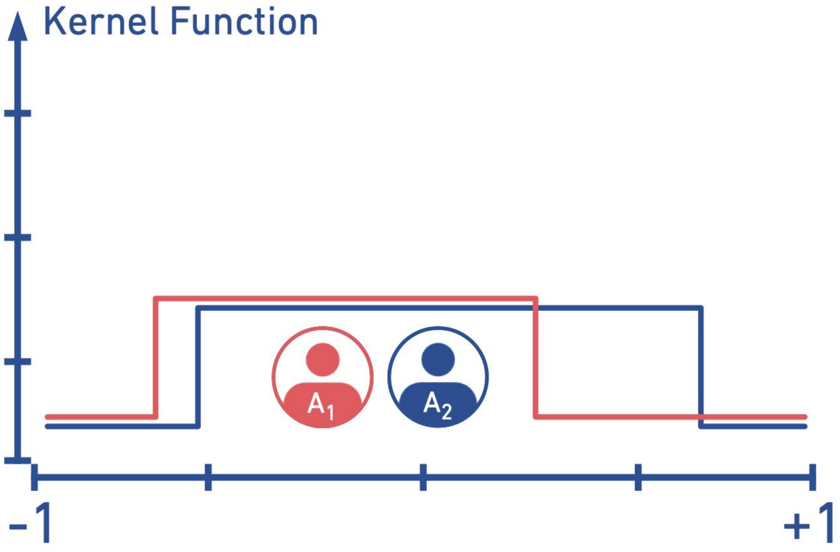
$$x := x + \mu \cdot k_{\theta}\left(x, x', \theta'\right) \cdot \left(x' - x\right)$$
$$x' := x' + \mu \cdot k_{\theta'}\left(x', x, \theta\right) \cdot \left(x - x'\right)$$

$$\theta := \theta + \mu \cdot k_{\theta}\left(x, x', \theta'\right) \cdot \left(\theta' - \theta\right)$$
$$\theta' := \theta' + \mu \cdot k_{\theta'}\left(x, x', \theta\right) \cdot \left(\theta - \theta'\right)$$

Related Work: The Deffuant Model (4/6)

$$k_\theta\left(x, x', \theta'\right) = h_\theta\left(x, x'\right) = 1 \text{ if } \left|\mathrm{x} - \mathrm{x}'\right| < \theta$$
$$k_\theta\left(x, x', \theta'\right) = h_\theta\left(x, x'\right) = 0 \text{ otherwise}$$

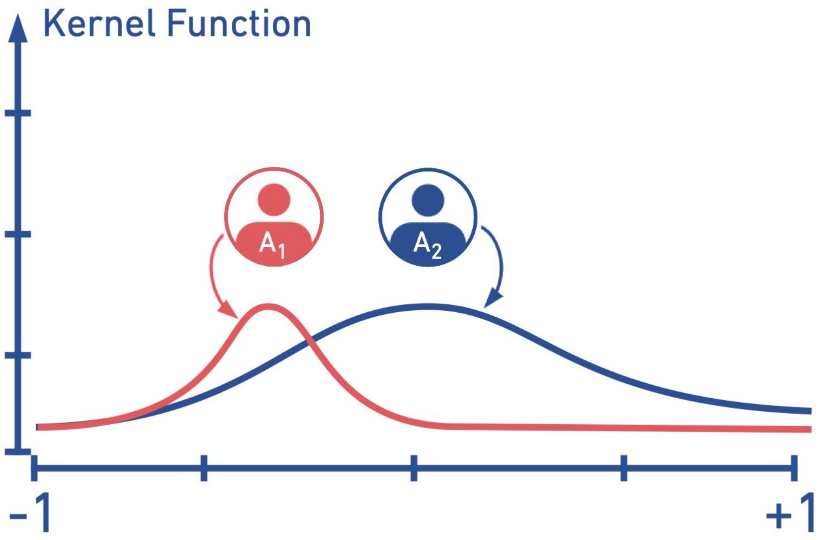
Heaviside kernel function:



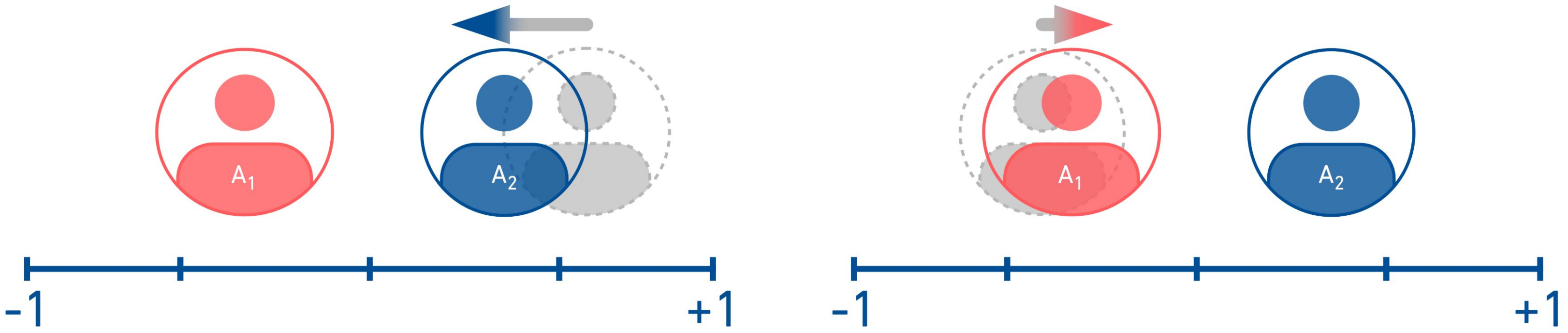
Related Work: The Deffuant Model (5/6)

$$k_\theta\left(x, x', \theta'\right) = g_\theta\left(x, x'\right) = \exp\left(-\left(\frac{x - x'}{\theta}\right)^2\right)$$

Gaussian kernel function:



Related Work: The Deffuant Model (6/6)



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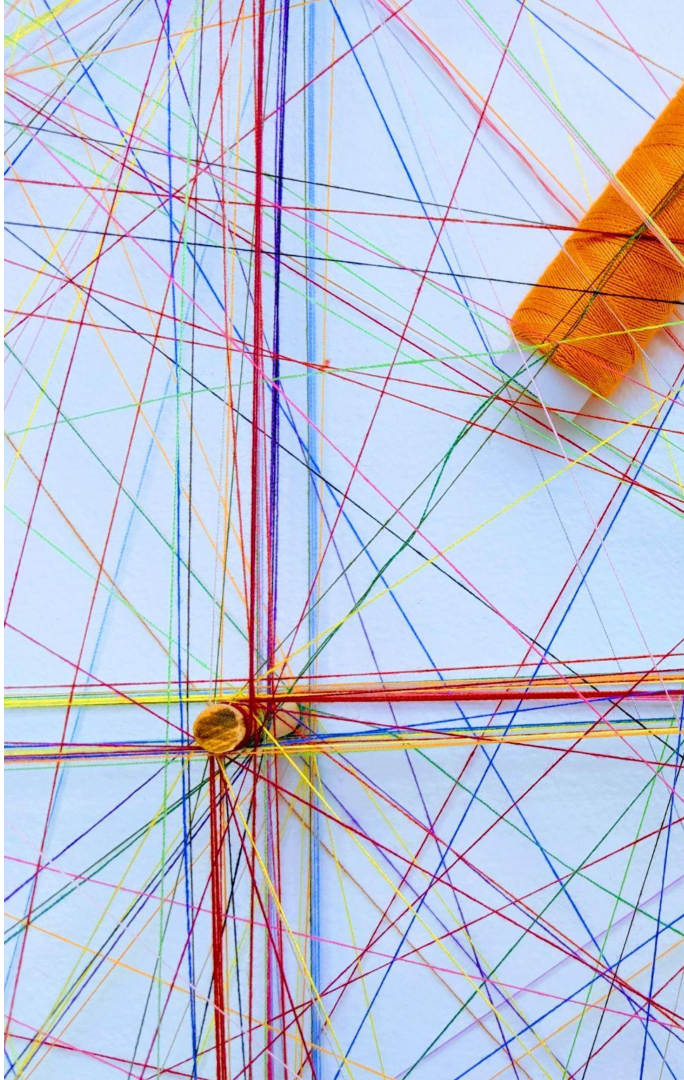
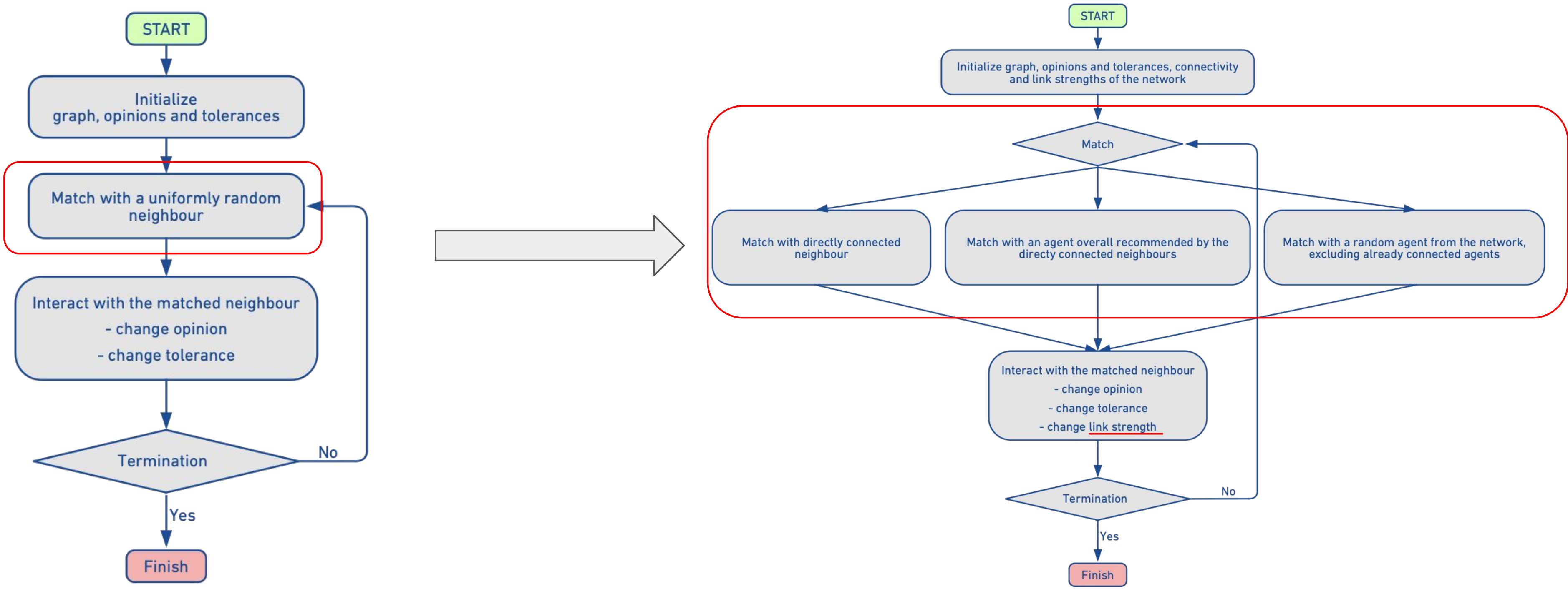
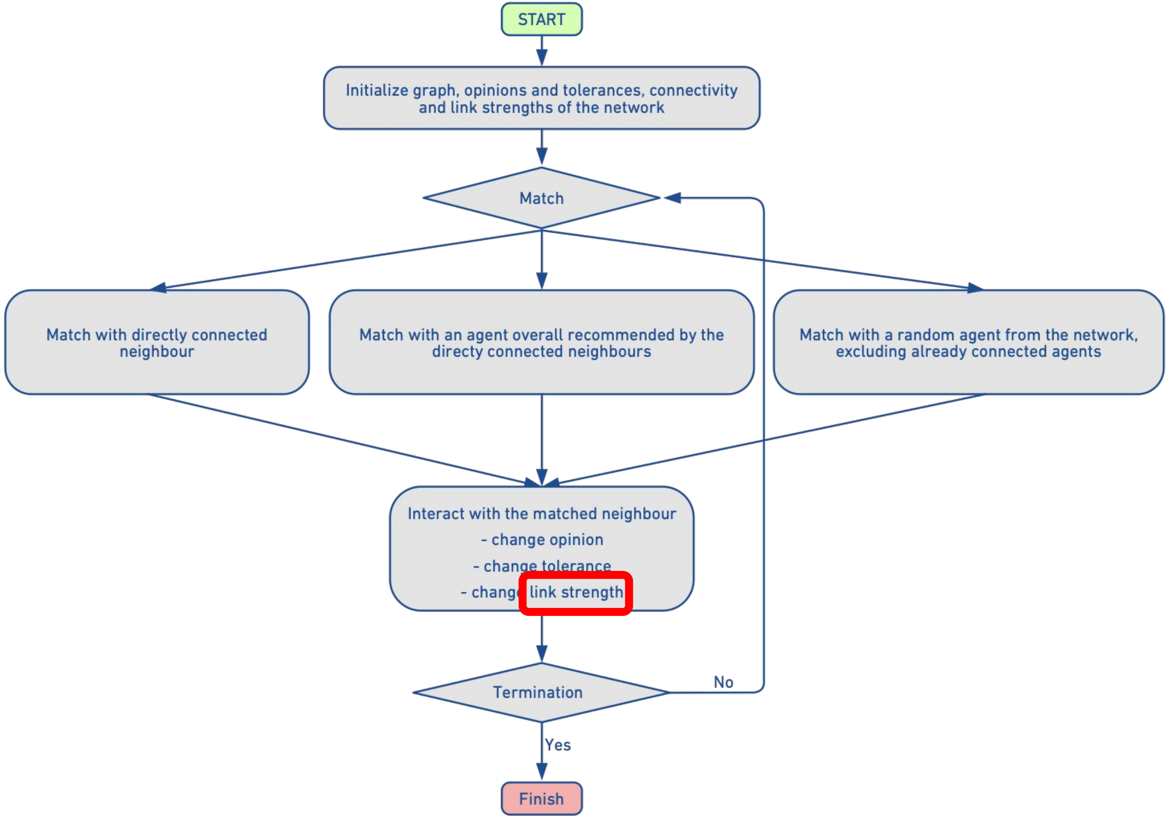


Our Model



START
Initialize
graph, opinions and tolerances
Match with a uniformly random neighbour
Interact with the matched neighbour
- change opinion
- change tolerance
Termination
No
Yes
Finish
START
Initialize graph, opinions and tolerances, connectivity and link strengths of the network
Match
Match with directly connected neighbour
Match with an agent overall recommended by the directy connected neighbours
Match with a random agent from the network, excluding already connected agents
Interact with the matched neighbour
- change opinion
- change tolerance
- change link strength
Termination
No
Yes
Finish

Our Model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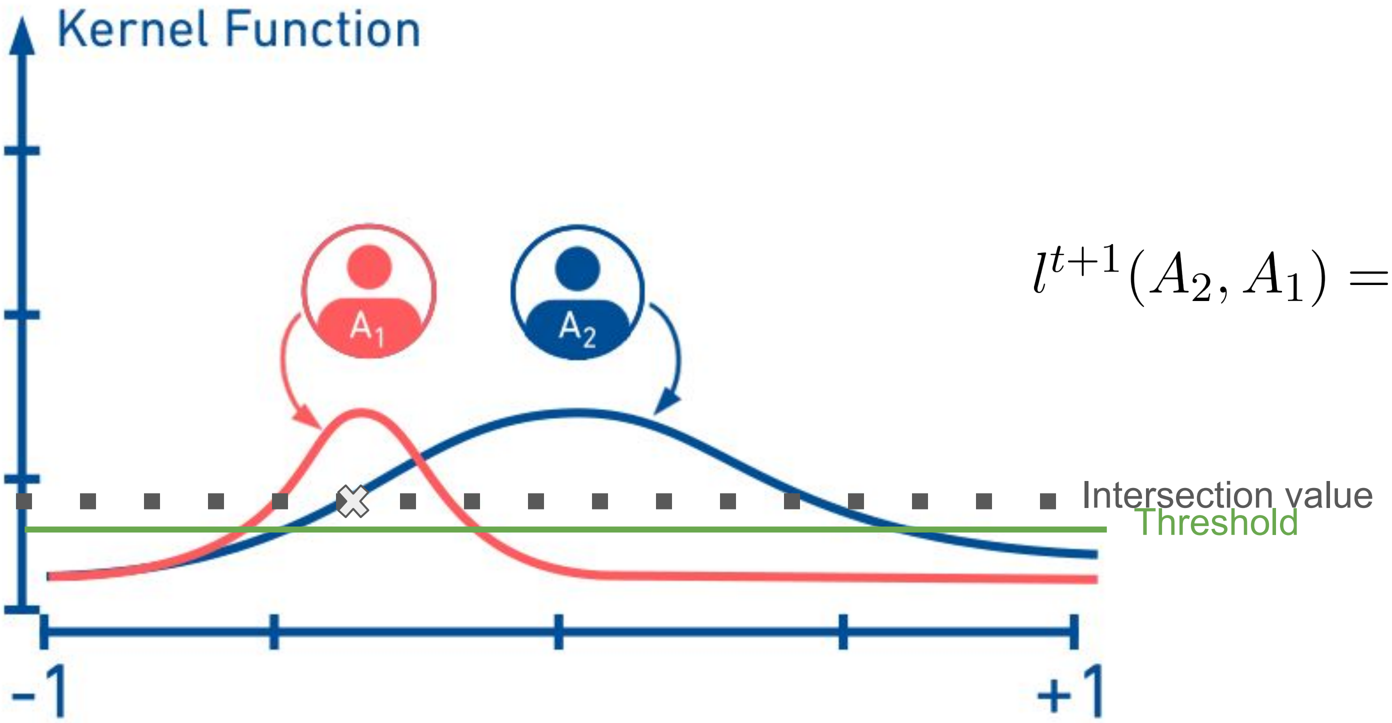
Link strength: Assumptions

- Models the degree of trust an agent has towards another agent.
- Persons prefer to meet people they are closer to more often (homophily).
- A person’s closeness with another person increases when they have a pleasant interaction, while they become more distant the more unpleasant interactions they have with them.
- A person has a pleasant interaction with their interlocutor if they agree at least at a certain level.
- A person retains the “history” of interactions they’ve had with other people in the memory, to the point where the person can view them in a neutral manner, or even in a negative light.

Link strength: Features

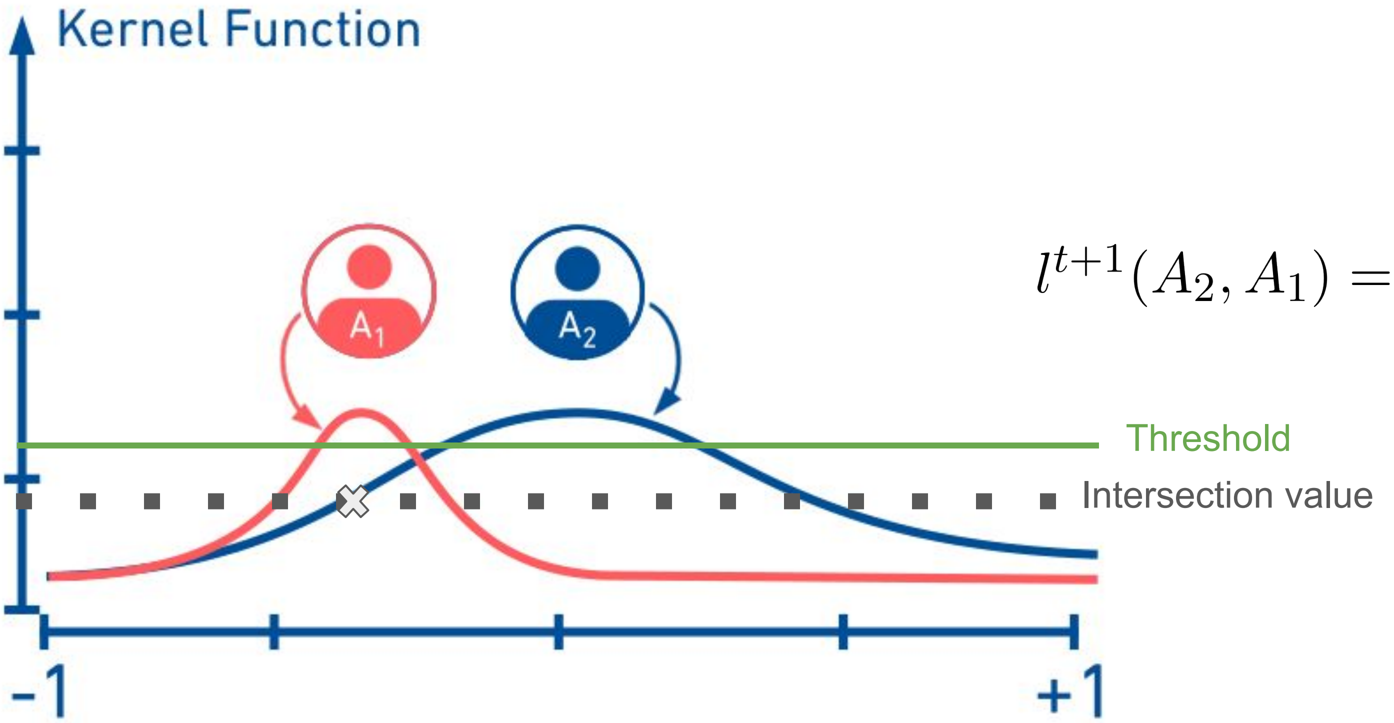
1. Interactions do not happen with a uniform distribution anymore.
2. Network acquires dynamic properties and connectivity.

Link strength: Change



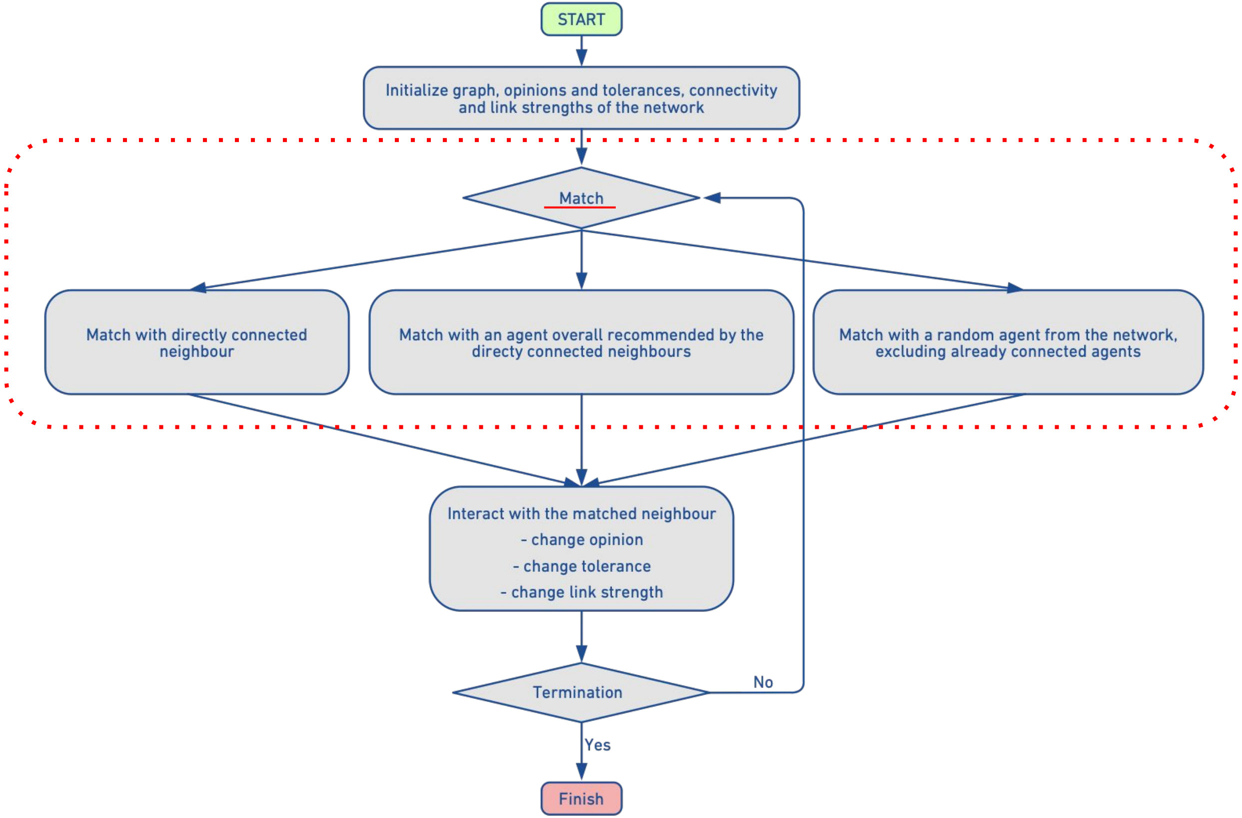
$$l^{t+1}(A_2, A_1) = l^t(A_2, A_1) + 1$$

Link strength: Change



$$l^{t+1}(A_2, A_1) = l^t(A_2, A_1) - 1$$

Our Model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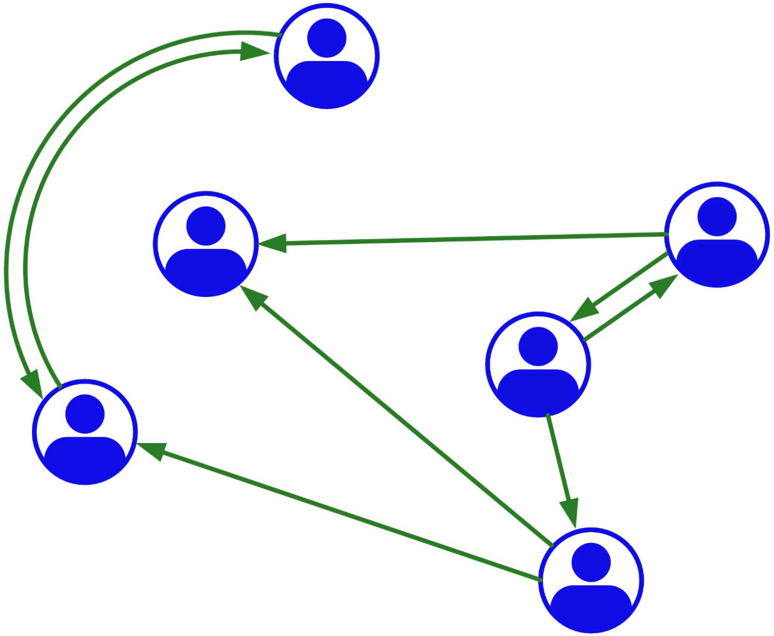
Match with a random agent from the network, excluding already connected agents
Interact with the matched neighbour
- change opinion
- change tolerance
- change link strength
Termination
No
Yes
Finish

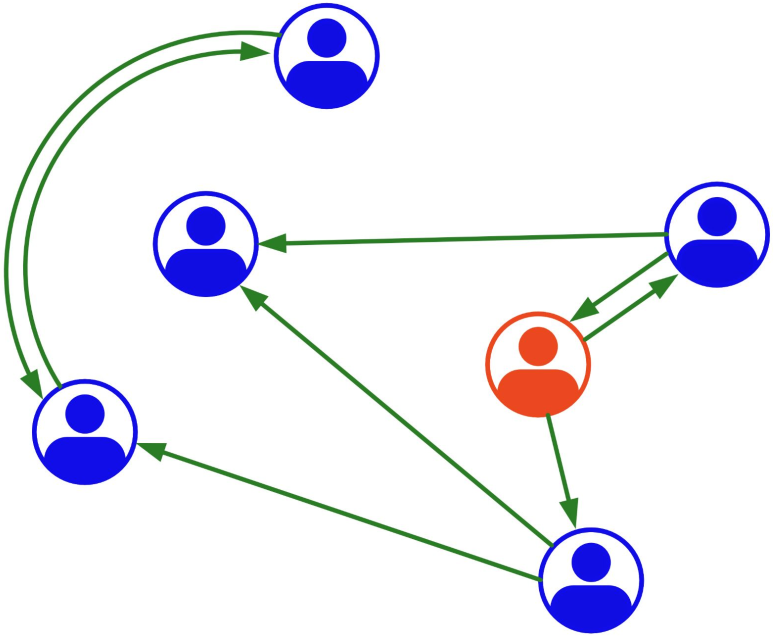
Our Model: Matching scheme

1. Friend
2. Recommendation from friends
3. Random

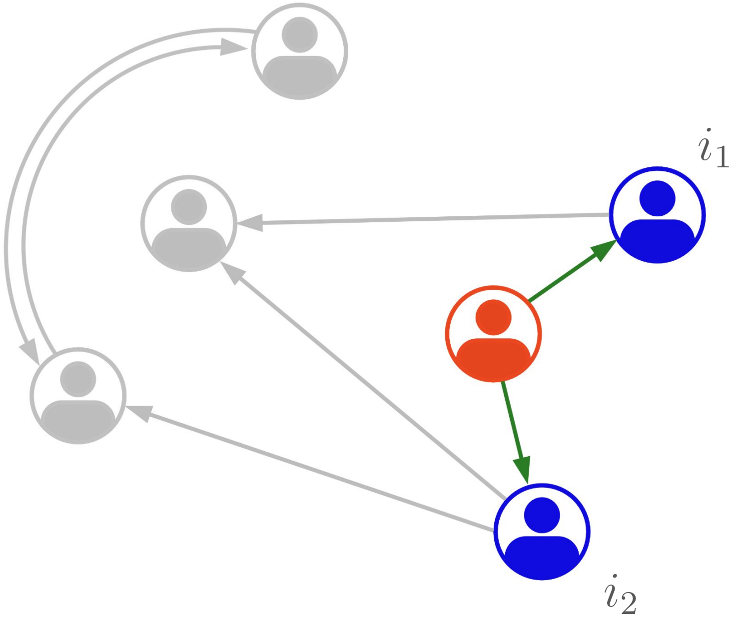
Toy Problem: the graph



Toy Problem: the graph

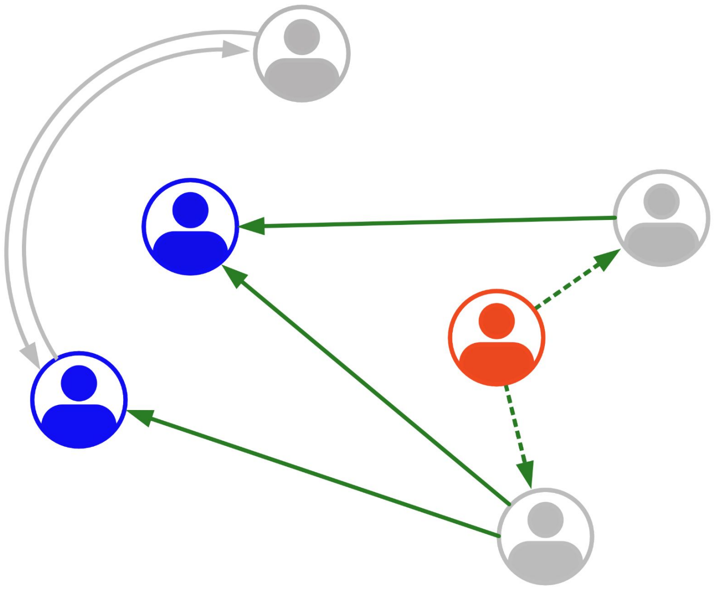


Matching scheme case 1: Friend



$$p_a(i) = \frac{\max\{0,\ l(a,i)\}}{\sum_{j \in \mathcal{N}_a} \max\{0,\ l(a,j)\}\})}$$

Matching scheme case 2: Recommendation



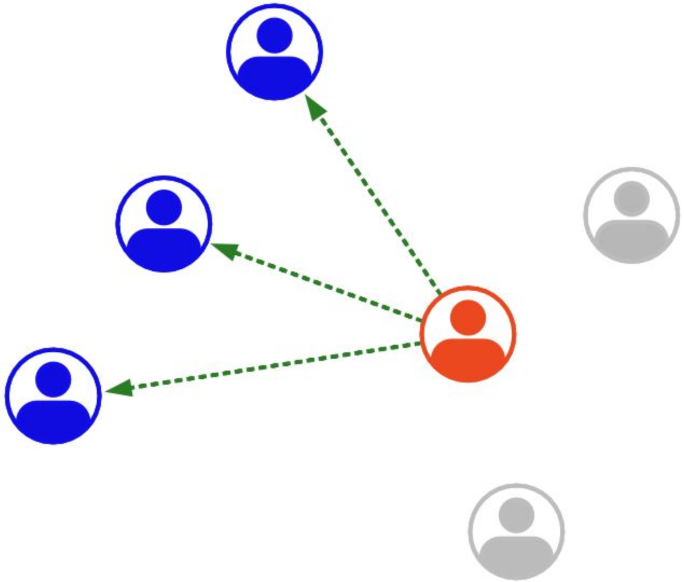
Suppose link strength matrix L

$$p_{a}(k) = \frac{\max(0,\ \sum_j \max\{0,\ l_{aj}\} l_{jk})}{\sum_{\kappa} \max(0,\ \sum_j \max\{0,\ l_{aj}\} l_{j\kappa})}$$

or

1. Consult your friends $\max\{0, l_{aj}\}$
2. Listen to their assessment (link strength) about other *people* (not only about their friends) $l_{j,k}$
3. Consider to meet people whose net assessment is positive. $\sum_j l_{aj} l_{jk} > 0$

Matching scheme 3: Random agent



$$p_{a}(i) = \begin{cases} \dfrac{1}{\sum_{j \notin \mathcal{N}_{a}} 1} & \text{if } \nexists l(a, i) \\ 0 & \text{otherwise} \end{cases}$$

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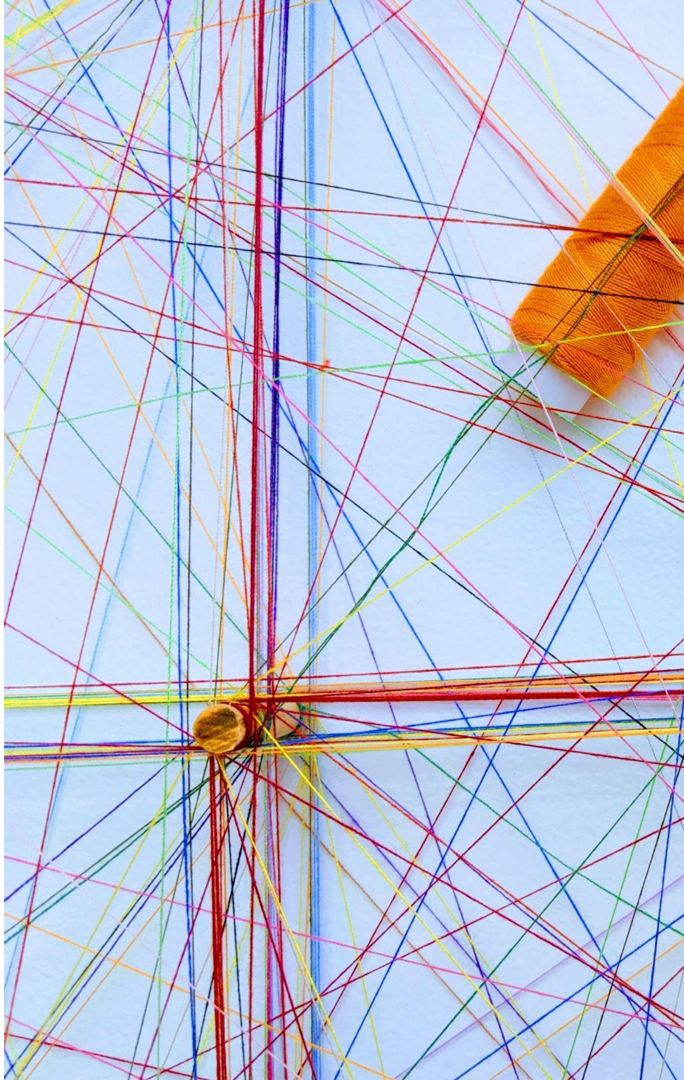
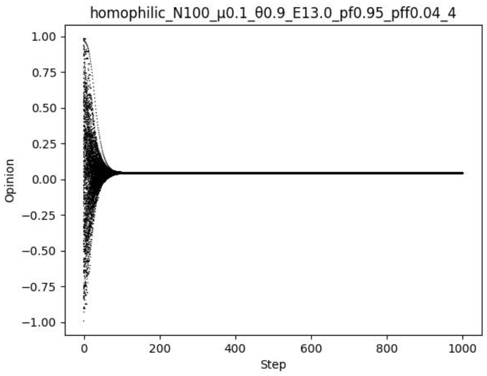
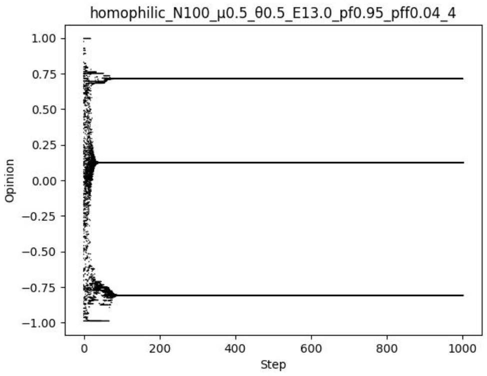


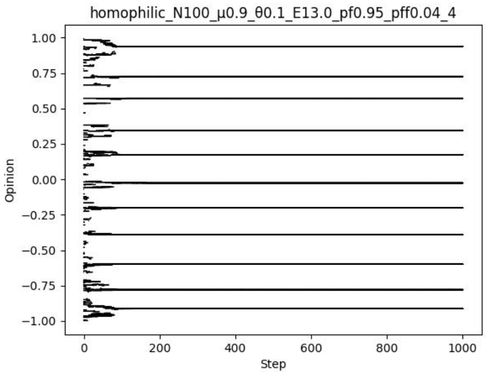
Results (1/7) - Types of convergence



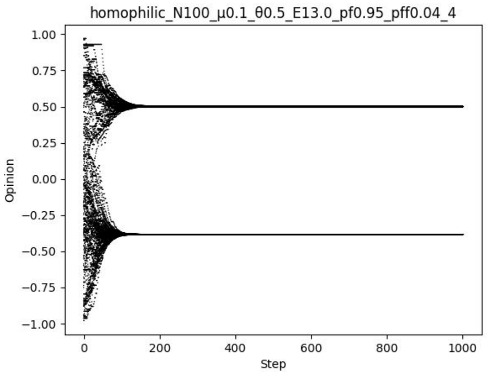
Single opinion convergence outcome



Intermediate between single and double opinion convergence outcome



Moderate opinion convergence outcome

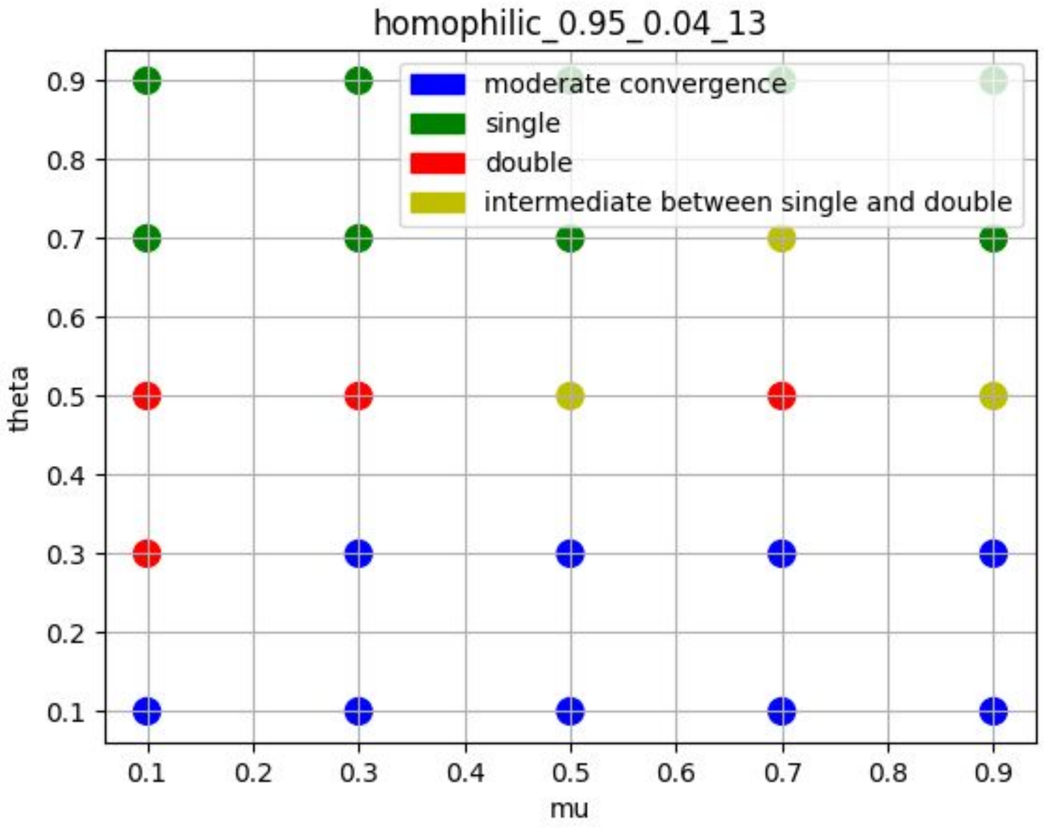


Double opinion convergence outcome

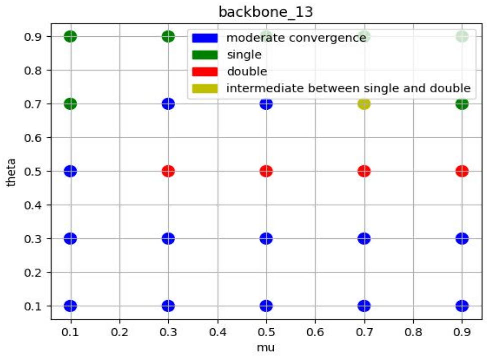
Results (2/7) - Phase diagram

- Bounded confidence parameter (theta) has the most influence

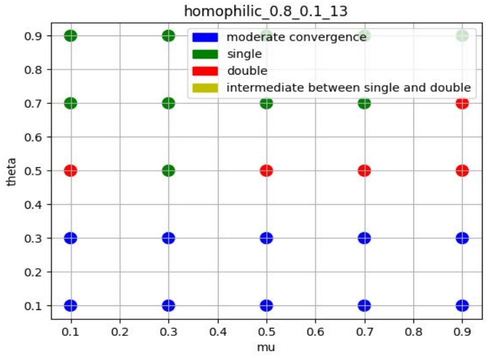
- The more people get influenced at each encounter (mu increasing) the faster they create groups with strong opinion, even if the effect is slight

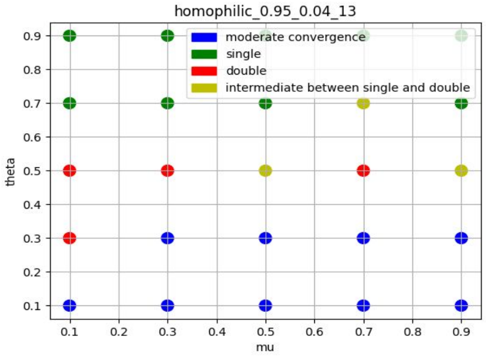


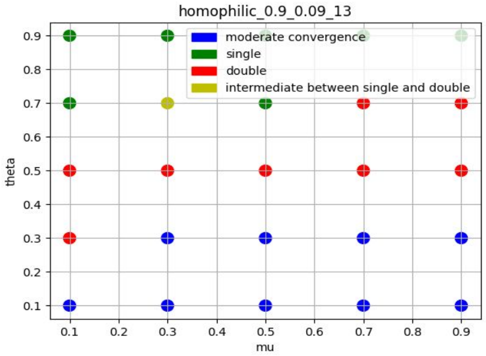
Results (3/7) - Comparison classic/experiential



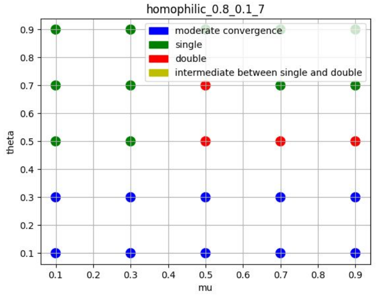
- The homophilic behavior seems to reinforce this early stage community formation, leading to globally clearer and more extreme outcomes

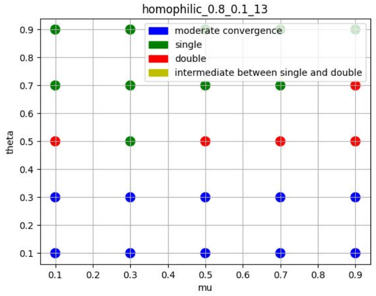


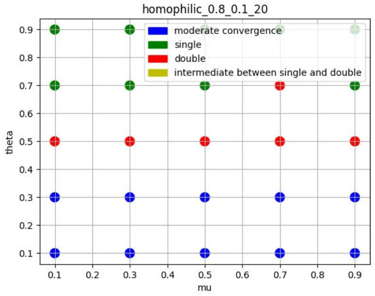


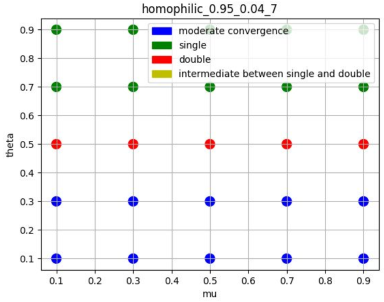


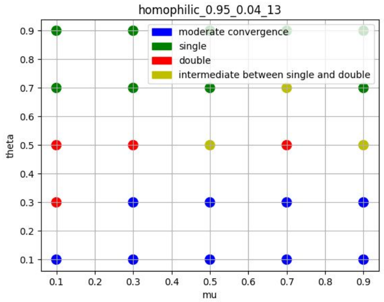
Results (4/7) - Initial graph connectivity influence

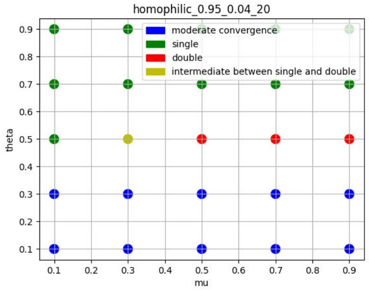






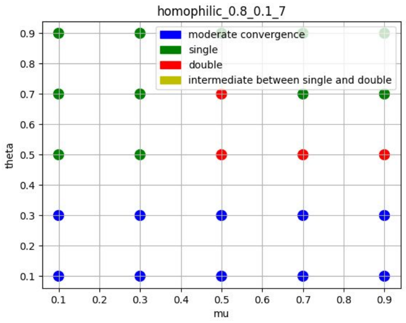


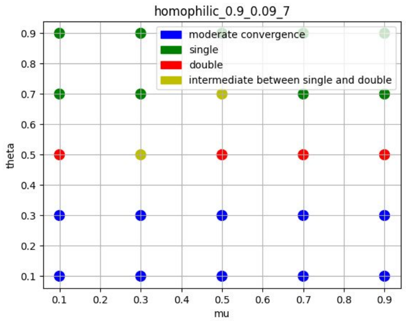


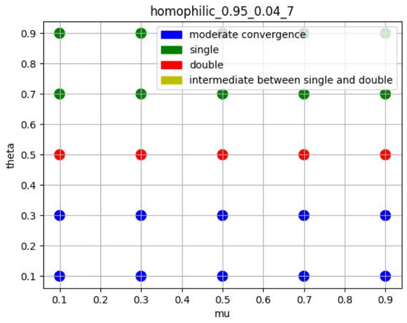


- Unclear influence of the parameter
- Hypothesis : increasing this parameter increases the size of initial subcommunities, favorizing the strength and number of initial subgroup of similar opinions, but does not influence much late opinion distribution

Results (5/7) - Influence of individual tendencies

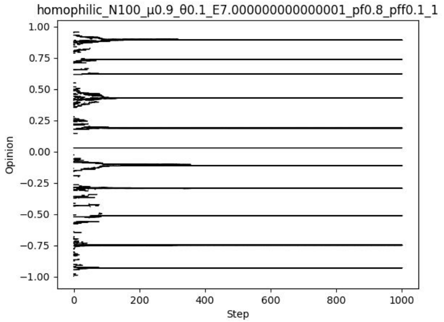


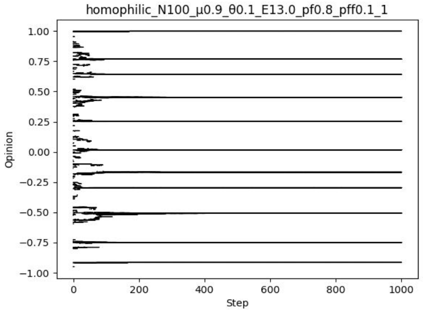


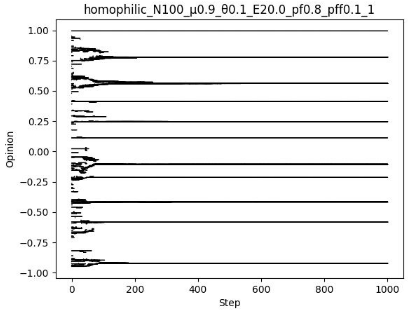


- Dictates the dedication of the agents to their community
- Similarly to the initial number of edges, might mainly affect the initial formation of opinion subgroups
- The proportion of random people encounters seems to have the most influence on the outcome:
  - makes communities more “open-minded” and favorizes smaller number of groups in final state

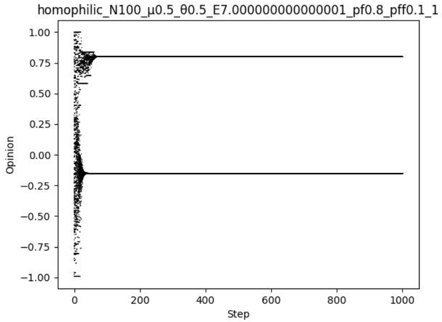
Results (6/7) - Subcommunity dynamics - Influence of initial number of edges

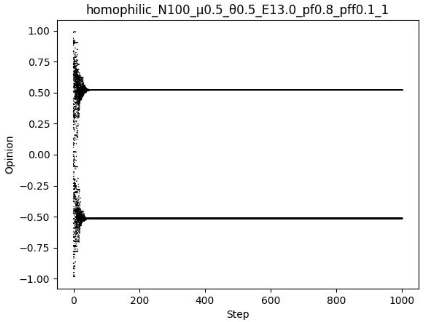


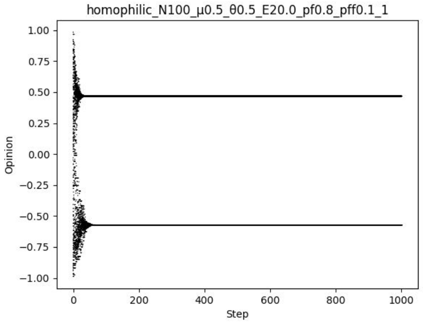




- Cases of moderate convergence

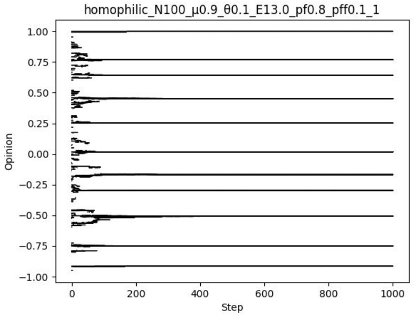


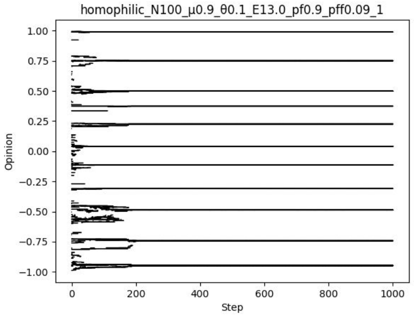


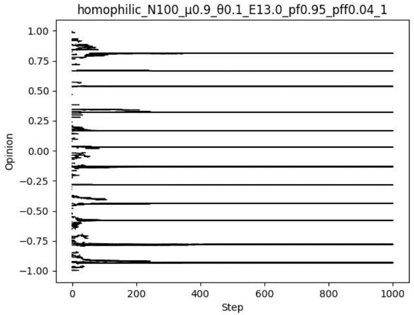


- Cases of double convergence

Results (7/7) - Subcommunity dynamics - Influence of individual tendencies







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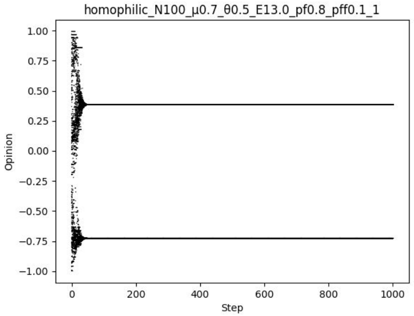

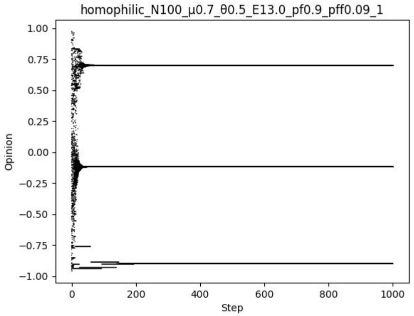

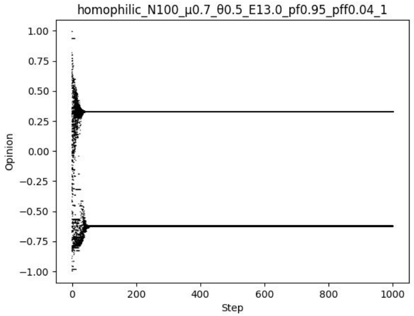

- Cases of double convergence

Discussion

- In the end, the θ parameter remains the most important one, determining most of the outcome of the simulation

- Other parameters tend to have initial opinion dynamics strengthening effect, but with low influence, and unclearly impacts converged results

- Ideas to go further :
  - More thorough initial subcommunities formation characterisation
  - Look at speed of convergence
  - Make experiments with unconnected initial graphs
  - Increase precision and number of experiments
  - Make the bounded confidence parameter depend on the graph closeness between agents during an encounter

Conclusion

- New kind of model simulating the individual agents' will when choosing who to interact with

- Overall little influence of the new model over the outcomes

- Traces of interesting behavior during early stages

- Improvements required for seeing the full extent of this new behavior

Thank you for your time!
Questions?