



# Surprising Effects of Inhomogeneity on Opinion Dynamics

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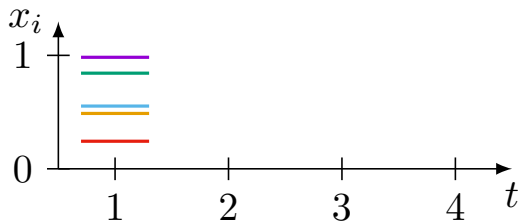
# Introduction

- ▶ Opinion dynamics  
evolution of opinions in a society of agents with time
- ▶ Social influence  
agents communicate and their opinion become more similar
- ▶ Bounded confidence  
very dissimilar agents do not have influence

Can we observe complex emergent behavior?

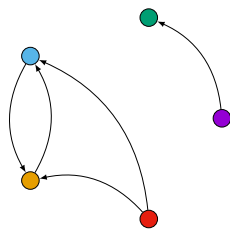
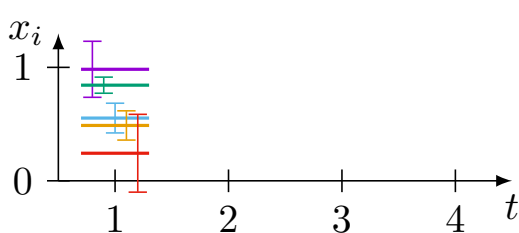
# Hegselmann-Krause bounded confidence model

- ▶  $N$  agents
- ▶ each with opinions  $x_i \in [0, 1]$
- ▶ each with confidence  $\varepsilon_i \in [0, 1]$
- ▶ neighbors are similar agents  $j$ , with  $|x_i - x_j| \leq \varepsilon_i$
- ▶ compromise with your neighbors  $x_i(t+1) = \frac{1}{|\mathcal{N}|} \sum_{j \in \mathcal{N}} x_j(t)$
- ▶ possible stationary states: *consensus* or *fragmentation*
- ▶ measure mean size of largest cluster  $\langle S \rangle$  to detect consensus



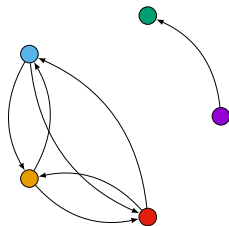
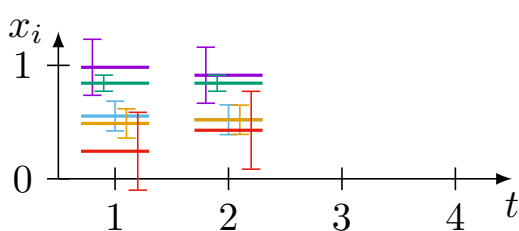
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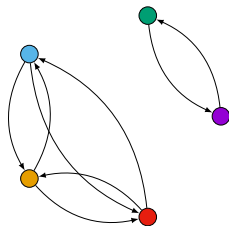
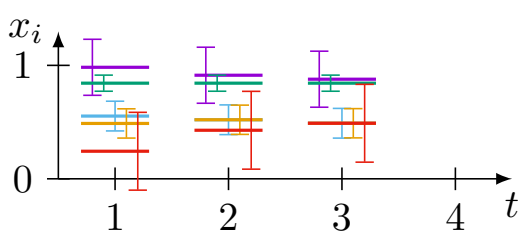
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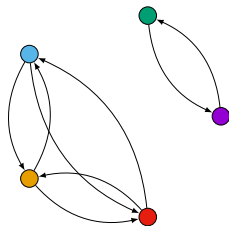
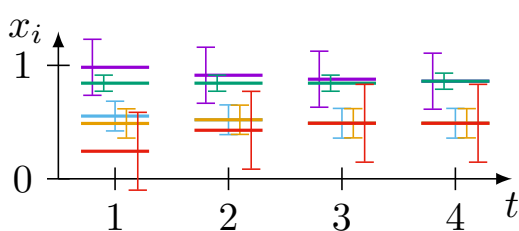
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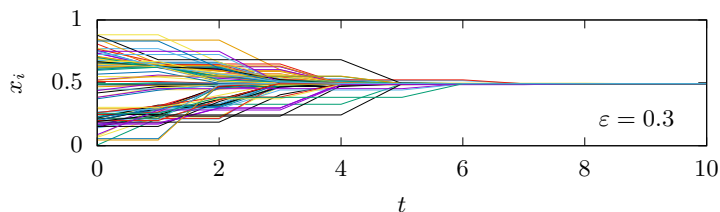
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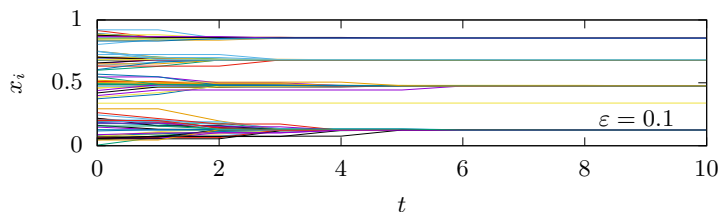
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# For which $\varepsilon_i$ do we expect consensus?

- ▶  $\varepsilon_i = \varepsilon \gtrsim 0.2$  always consensus (for large  $N$ ) [1]
- ▶ larger  $\varepsilon_i$  typically lead faster to consensus

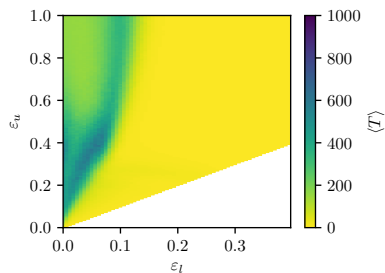
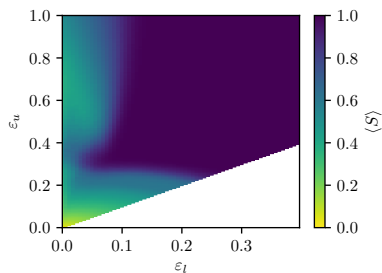
Which influence has heterogeneity in  $\varepsilon_i$ ?

- ▶ bimodal  $\varepsilon_i \in \{\varepsilon_1, \varepsilon_2\}$  for small systems or related models, suggest complex behavior
- ▶ Will this be stronger for stronger inhomogeneity  $\varepsilon_i \in U(\varepsilon_l, \varepsilon_u)$ ?
- ▶ Will it be preserved for large  $N$ ?

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[1] Hegselmann, Krause, 2002

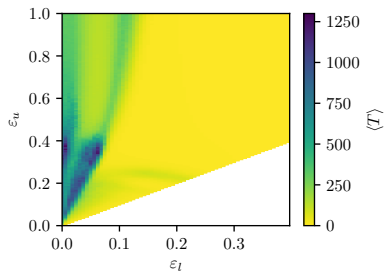
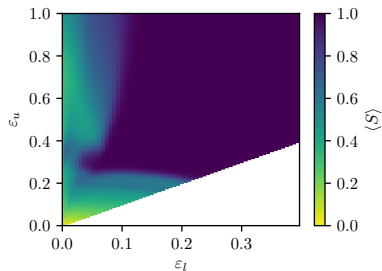
# Exploring the Landscape



$$N = 256$$

- ▶ Phase space with nonmonotonous, complex structure
- ▶ Consensus where mean confidence  $\varepsilon < 0.2$
- ▶ Surprising: Increasing confidence  $\varepsilon_u \Rightarrow$  loss of consensus
- ▶ All effects are stronger with larger systems

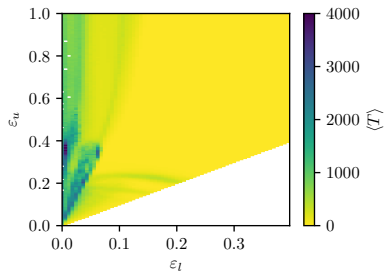
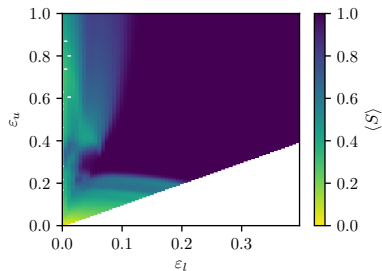
# Exploring the Landscape



$$N = 1024$$

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- ▶ Consensus where mean confidence  $\varepsilon < 0.2$
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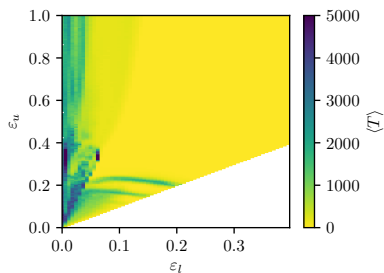
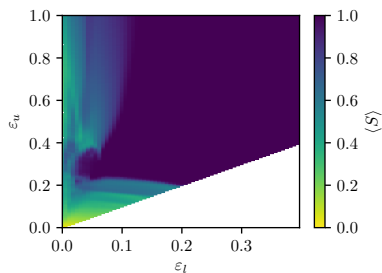
# Exploring the Landscape



$$N = 4096$$

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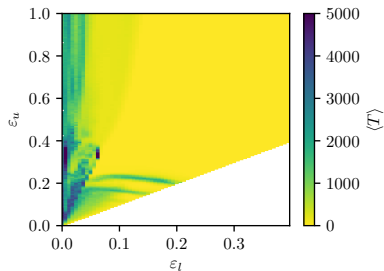
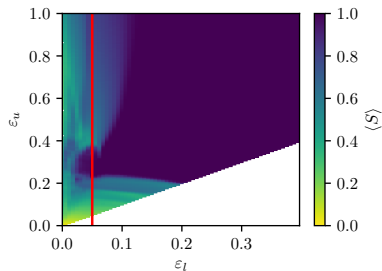
# Exploring the Landscape



$$N = 16384$$

- ▶ Phase space with nonmonotonous, complex structure
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# Exploring the Landscape

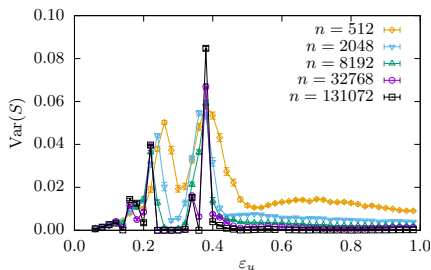
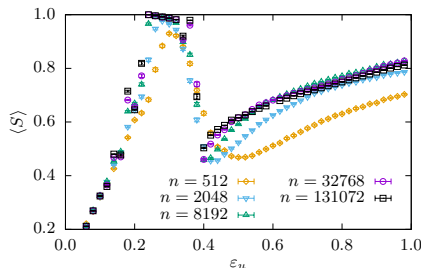


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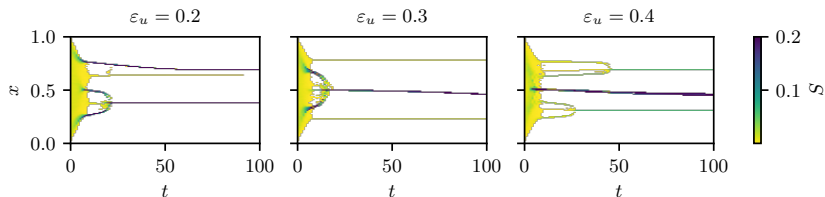
# Looking closer at the reentrant phase

- ▶  $\varepsilon_i \in [0.05, \varepsilon_u]$
- ▶ increasing upper bound  
→ more confident agents
- ▶ Two sharp flanks, getting sharper for larger systems
- ▶ Variance diverges at the flanks
- ▶ Phase transition to consensus and out of consensus





# How do confident agents destroy consensus?



- ▶ local clusters develop slowly and stabilize out of range  $\rightarrow$  fragmentation
- ▶ there are (almost) always 2 local clusters, which develop slowly
- ▶ attraction via moderate agents interacting with a small central cluster
- ▶ central cluster attracts confident agents very fast
- ▶ skeptic agents are left behind
- ▶ leads to fragmentation of the central cluster

# Conclusions

- ▶ heterogeneity facilitates consensus
- ▶ surprising: increasing the confidence can reduce the consensus
- ▶ read more: [arxiv:2001.06877](https://arxiv.org/abs/2001.06877)

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**Outlook** So, does heterogeneity always lead to more consensus in society?

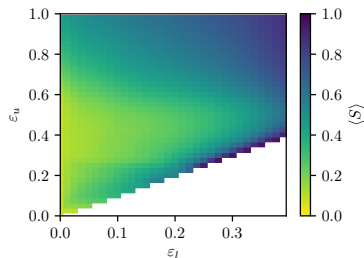
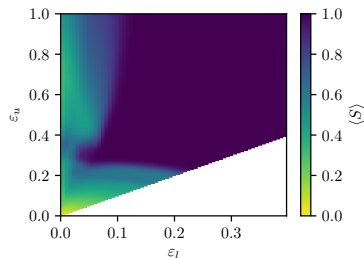
# Conclusions

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**Outlook** So, does heterogeneity always lead to more consensus in society?

Well, not necessarily.

introduction of a small cost:

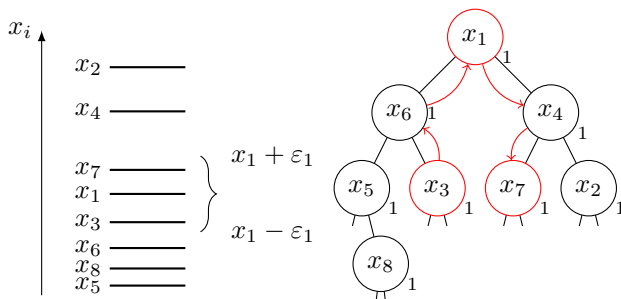


# What is the problem when simulating? Introducing a faster algorithm.

- ▶ At each time step each agent has to average over all neighbors  $\Rightarrow \mathcal{O}(N^2)$
- ▶ Introducing new algorithm
  - ▶ It is only necessary to touch the neighbors, which are far fewer for low  $\varepsilon_i$
  - ▶ Converged clusters look for another agent like a single agent with high weight
- ▶ allows us to gather good statistics for systems two orders of magnitude larger ( $N = 131072$ ) than what is typically studied

# Introducing a faster algorithm.

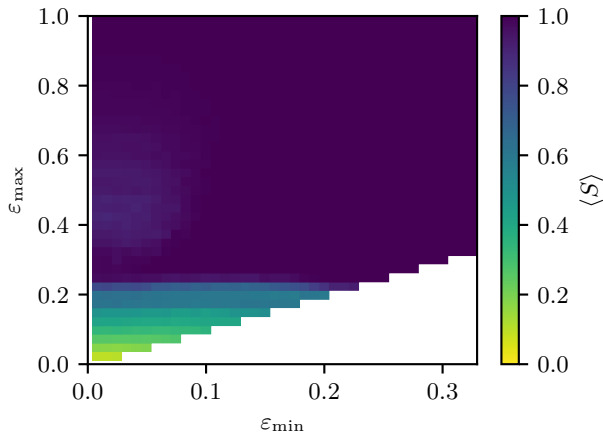
- ▶ Save all opinions in the system in a tree
- ▶ to average the neighbors of agent  $i$ 
  - ▶ find the smallest opinion  $x_j \geq x_i - \varepsilon_i$  in  $\mathcal{O}(\log(N))$
  - ▶ traverse the tree in order and stop averaging on encountering  $x_j \geq x_i + \varepsilon_i$
  - ▶ if a value  $x_j$  occurs more than once in the tree, assign it a weight



# What about other distributions of $\varepsilon_i$ ?

Bounded power law

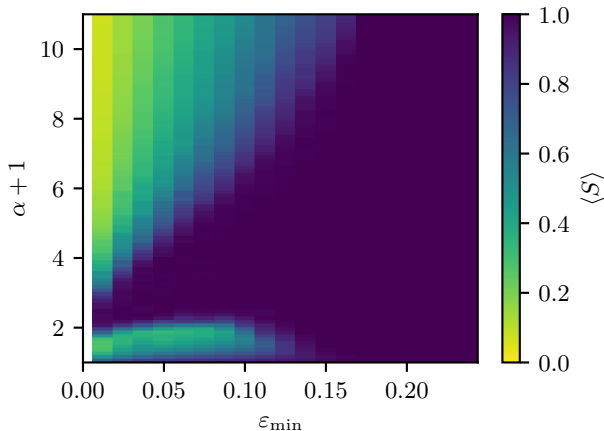
$$p(\varepsilon) = c\varepsilon^{-\gamma}$$



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Pareto

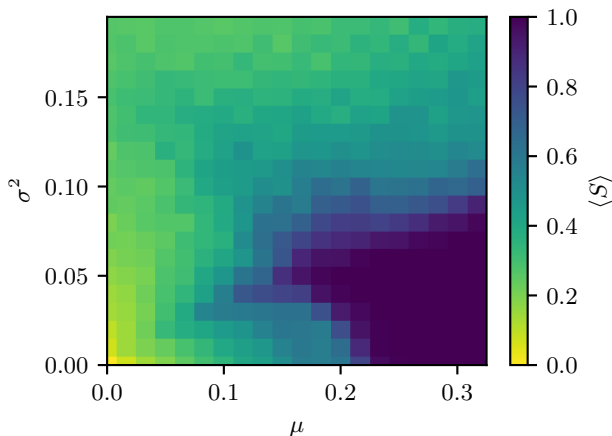
$$p(\varepsilon) = \frac{\alpha x_{\min}^\alpha}{x^{\alpha+1}}$$





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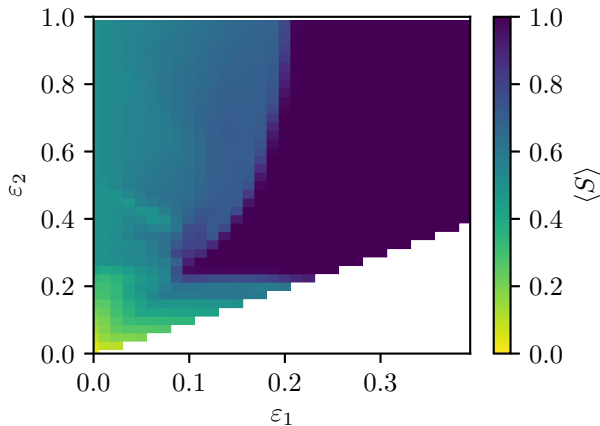
## Gaussian



# What about other distributions of $\varepsilon_i$ ?

Bimodal

$$p(\varepsilon) = \delta(\varepsilon - \varepsilon_1) + \delta(\varepsilon - \varepsilon_2)$$



# Mean Dynamics

