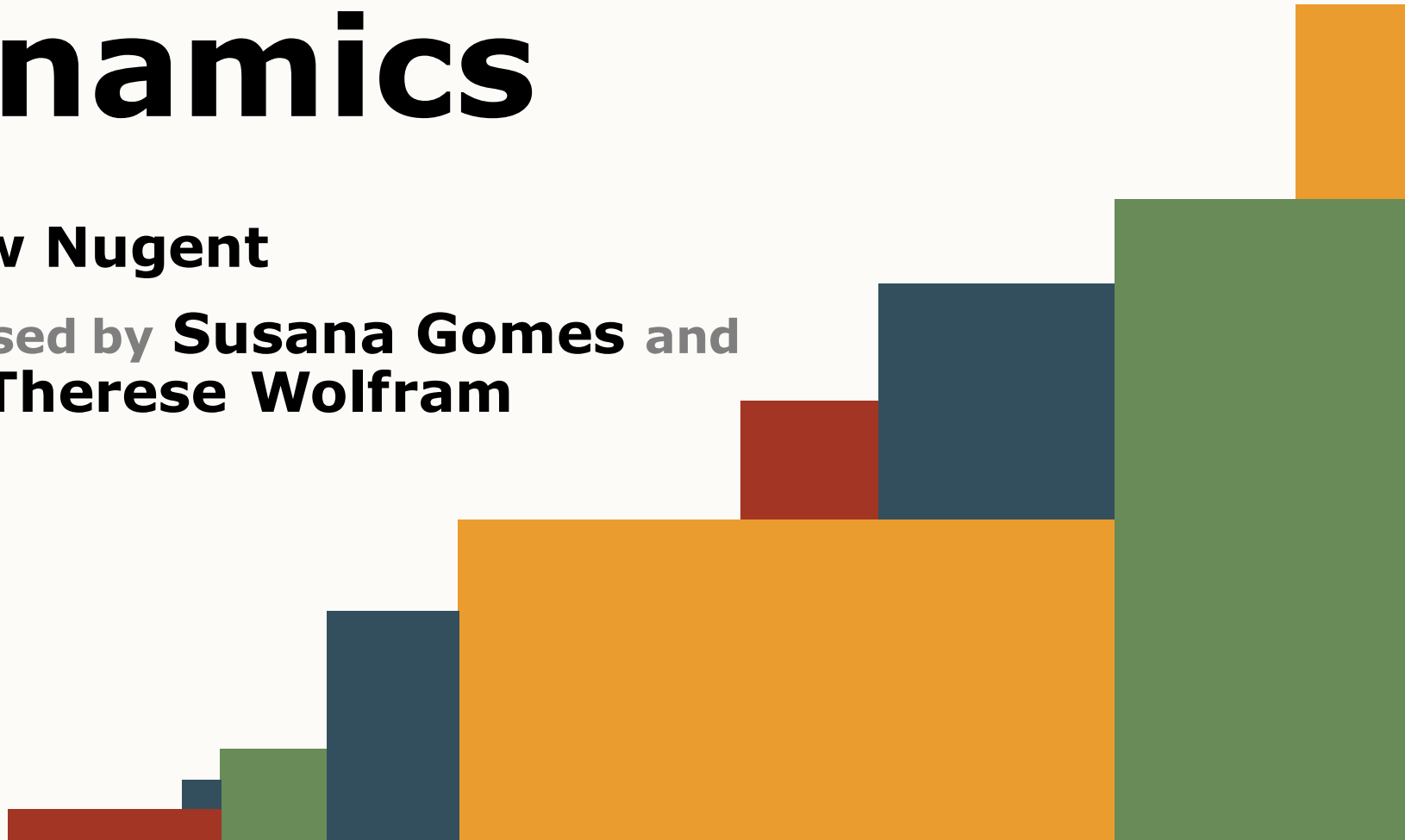


# Scaling in Opinion Dynamics

**Andrew Nugent**

Supervised by **Susana Gomes** and  
**Marie-Therese Wolfram**



# ODE model

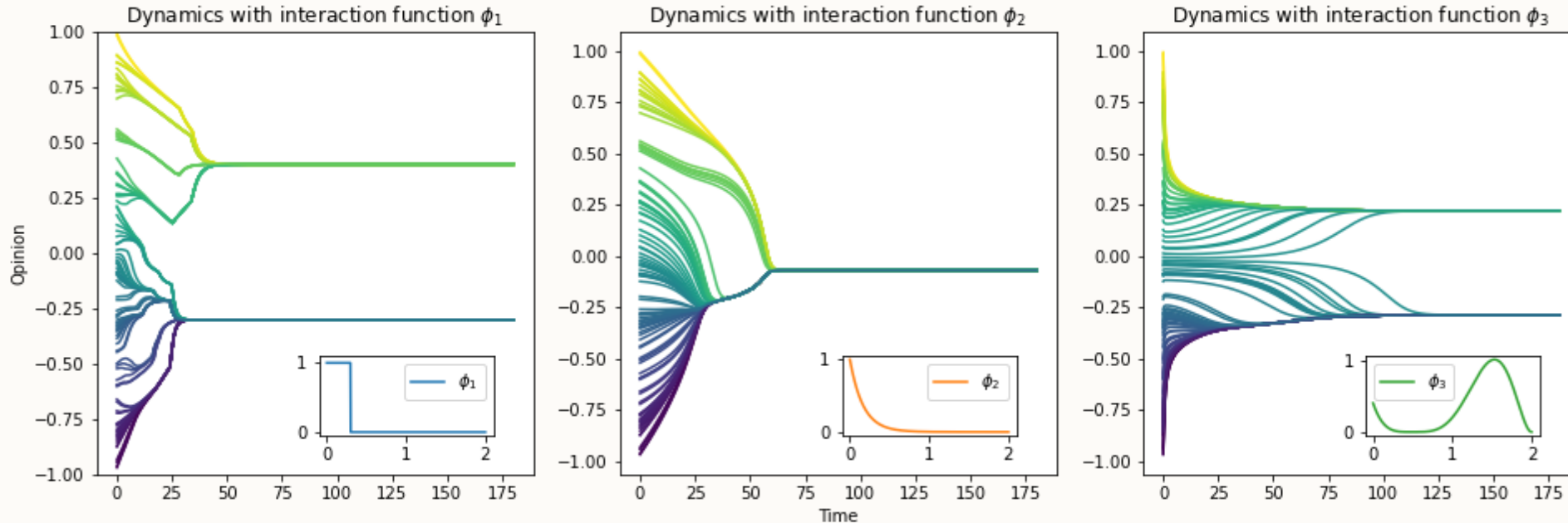
- Opinions in  $x_i \in [-1,1]$  for  $i = 1, \dots, N$ .
- A function  $\phi : \mathbb{R} \rightarrow [0, 1]$  determines how individuals weight each others' opinions.
- Opinions evolve according to:

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_{j=1}^N \phi(|x_j - x_i|) (x_j - x_i)$$

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# Unfortunately... reality

1. Social interactions are **discrete events**, meaning
2. We cannot interact with **everyone simultaneously**, so
3. The **order** of interactions makes a difference.
4. Also, interactions occur **randomly**.

# Unfortunately... reality

1. Social interactions are discrete events, meaning
  - ⊗ Social interactions happen **continuously** and
2. We cannot interact with everyone simultaneously, so
  - ⊗ Everyone interacts **simultaneously**, so
3. The order of interactions makes a difference.
  - ⊗ There is **no sequence** of interactions, and so **no order**.
4. Also, interactions occur randomly.
  - ⊗ Interactions are also **deterministic**.

# Agent-based model

1. Choose two individuals  $i$  and  $j$  uniformly at random with replacement.
2. They interact with probability  $p_{ij}(x)$ , with individual  $i$  updating their opinion according to:

$$x_i(t+h) = \begin{cases} x_i(t) + \mu^h (x_j(t) - x_i(t)) & \text{with probability } p_{ij}(x) \\ x_i(t) & \text{with probability } 1 - p_{ij}(x). \end{cases}$$

3. Repeating until time  $T$  is reached.

# Closer to reality

1. Social interactions are discrete events, meaning
  - ☑ Social interactions are **discrete events**.
2. We cannot interact with everyone simultaneously, so
  - ☑ Individuals interact **pairwise**, not globally.
3. The order of interactions makes a difference.
  - ☑ Interactions happen **in an order**.
4. Also, interactions occur randomly.
  - ☑ Interactions occur **randomly**.

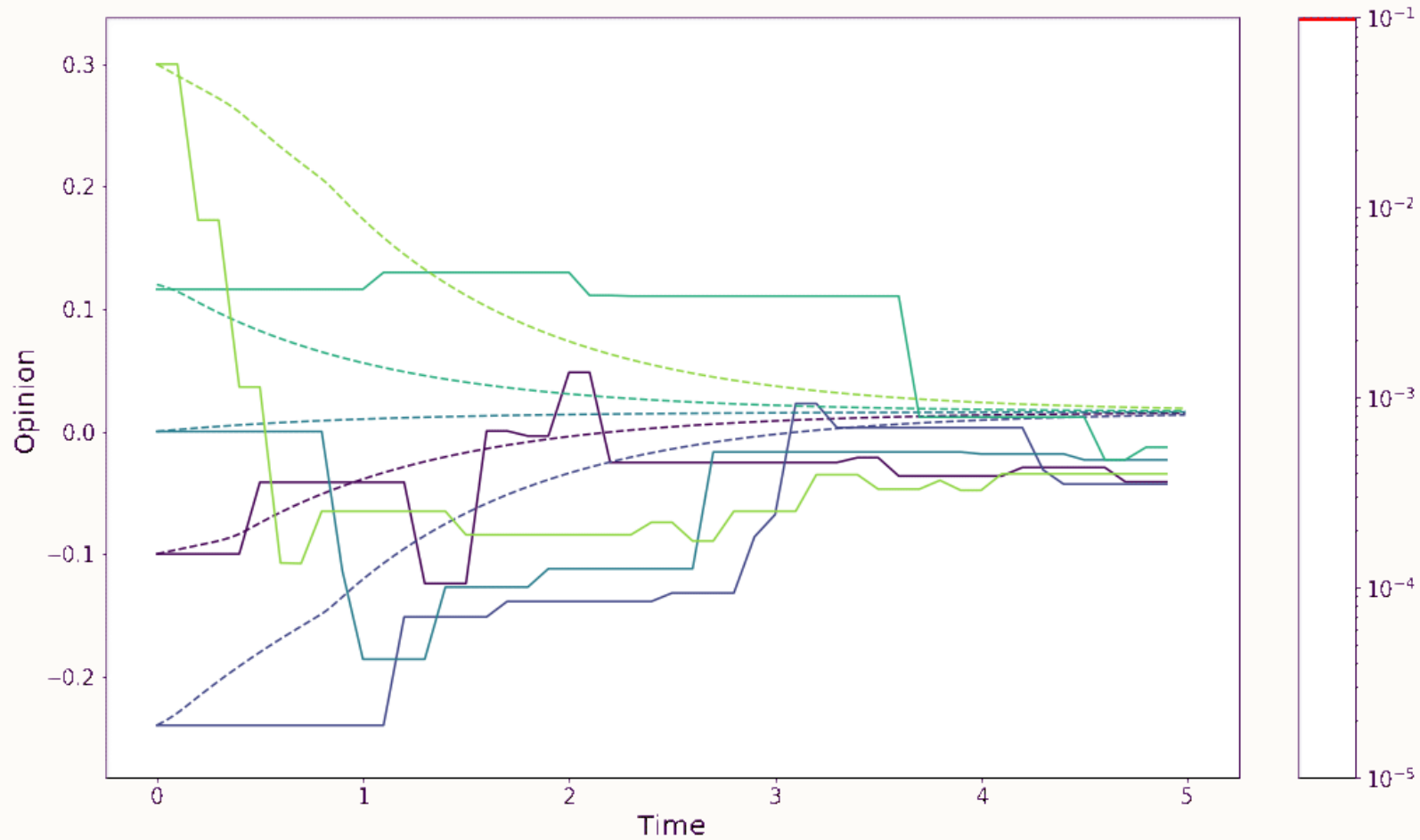
# Link to the ODE model?

## Claim:

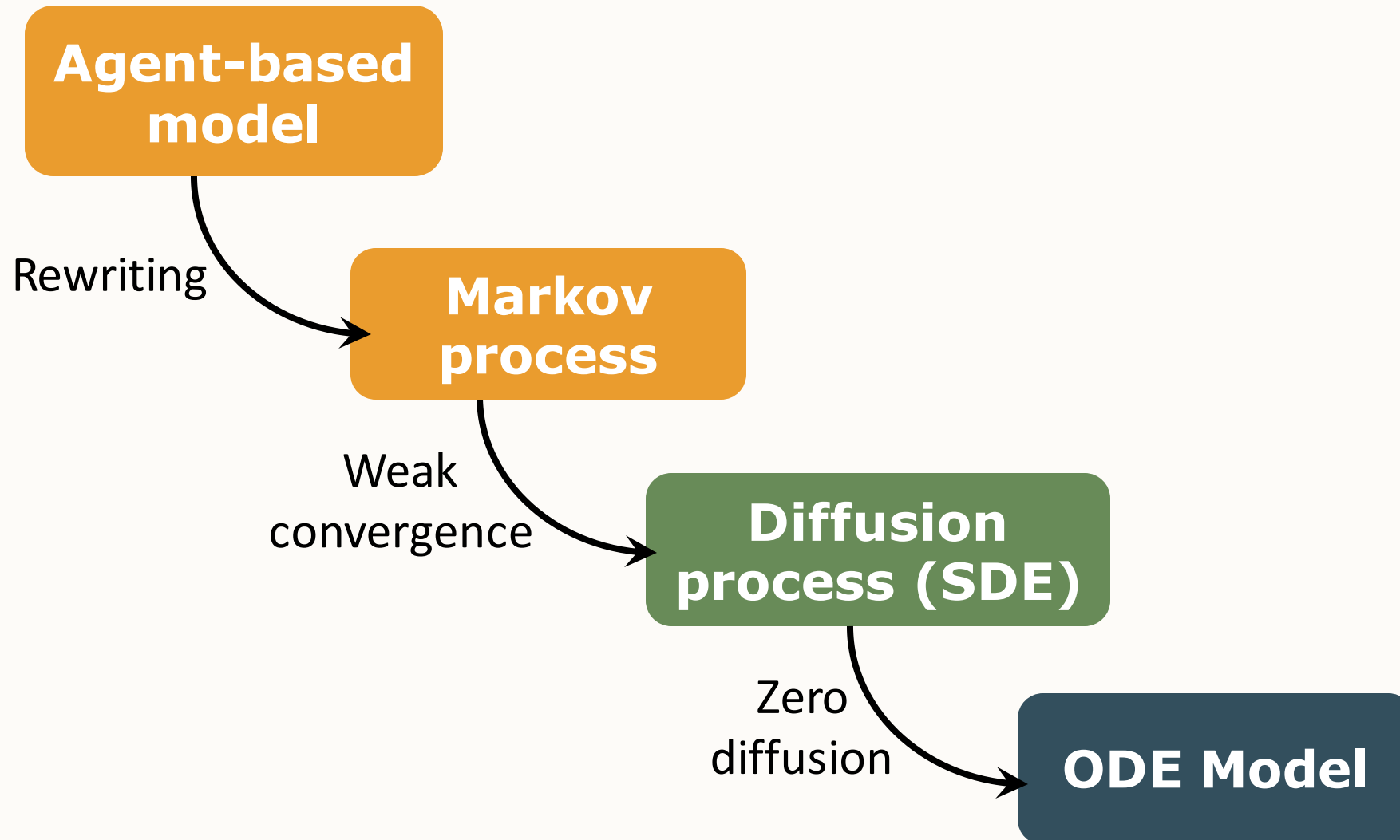
1. The ODE model can be obtained by rescaling the timestep  $h$  and update distance  $\mu^h = Nh$  of the ABM.
2. This means the ODE model approximates **small but frequent pairwise interactions**, so is a realistic model if these assumptions hold.



# Link to the ODE model?



# Establishing the link



# Markov process

Consider a discrete time Markov process with state space  $\mathbb{R}^N$ , time step  $h > 0$  and transition function:

$$\Pi^h(x, y) = \begin{cases} \frac{1}{N^2} p_{ij}(x) & \text{if } y = x + e_i \mu^h (x_j - x_i) \text{ for some } i \neq j, \\ \frac{1}{N} + \frac{1}{N^2} \sum_{i \neq j} (1 - p_{ij}(x)) & \text{if } y = x, \\ 0 & \text{otherwise.} \end{cases}$$

# Markov process

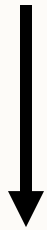
$$\Pi^h(x, y) = \begin{cases} \frac{1}{N^2} p_{ij}(x) & \text{if } y = x + e_i \mu^h (x_j - x_i) \text{ for some } i \neq j, \\ \frac{1}{N} + \frac{1}{N^2} \sum_{i \neq j} (1 - p_{ij}(x)) & \text{if } y = x, \\ 0 & \text{otherwise.} \end{cases}$$

# SDE system

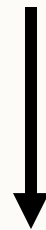
$$dX_i = b_i(X) dt + \sqrt{a_{ii}(X)} dW_i$$

# Markov process

$$\Pi^h(x, y) = \begin{cases} \frac{1}{N^2} p_{ij}(x) & \text{if } y = x + e_i \mu^h(x_j - x_i) \text{ for some } i \neq j, \\ \frac{1}{N} + \frac{1}{N^2} \sum_{i \neq j} (1 - p_{ij}(x)) & \text{if } y = x, \\ 0 & \text{otherwise.} \end{cases}$$



**Approximating  
generator**



# SDE system

$$dX_i = b_i(X) dt + \sqrt{a_{ii}(X)} dW_i$$

# Approximating generator

We calculate the mean and variance of increments to **approximate the drift and diffusion terms** of an SDE.

$$b_i^h(x) = \frac{1}{h} \int_{\mathbb{R}^N} (y_i - x_i) \Pi^h(x, dy)$$

$$a_{ij}^h(x) = \frac{1}{h} \int_{\mathbb{R}^N} (y_i - x_i)(y_j - x_j) \Pi^h(x, dy)$$

**A slight detour into  
generators...**

$$\begin{aligned}
(\mathcal{L}f)(x) &= \lim_{h \downarrow 0} \frac{1}{h} \mathbb{E}[f(X(h)) - f(x) \mid X_0 = x] \\
&\approx \lim_{h \downarrow 0} \left( f'(x) \frac{1}{h} \mathbb{E}[X(h) - x \mid X_0 = x] + \frac{f''(x)}{2} \frac{1}{h} \mathbb{E}[(X(h) - x)^2 \mid X_0 = x] \right) \\
&\approx \lim_{h \downarrow 0} \left( f'(x) \frac{1}{h} \int_{\mathbb{R}} (y - x) \Pi^h(x, dy) + \frac{f''(x)}{2} \frac{1}{h} \int_{\mathbb{R}} (y - x)^2 \Pi^h(x, dy) \right) \\
&\approx \lim_{h \downarrow 0} \underbrace{\left( f'(x) b^h(x) + \frac{f''(x)}{2} a^h(x) \right)}
\end{aligned}$$

$$dX = b^h(X) dt + \sqrt{a^h(X)} dW$$



$$\begin{aligned}
(\mathcal{L}f)(x) &= \lim_{h \downarrow 0} \frac{1}{h} \mathbb{E}[f(X(h)) - f(x) \mid X_0 = x] \\
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&\approx \underbrace{\lim_{h \downarrow 0} \left( f'(x) b^h(x) + \frac{f''(x)}{2} a^h(x) \right)}_{dX = b(X) dt + \sqrt{a(X)} dW}
\end{aligned}$$

# And we're back

We calculate the mean and variance of increments to **approximate the drift and diffusion terms** of an SDE.

$$b_i^h(x) = \frac{1}{h} \int_{\mathbb{R}^N} (y_i - x_i) \Pi^h(x, dy)$$

$$a_{ij}^h(x) = \frac{1}{h} \int_{\mathbb{R}^N} (y_i - x_i)(y_j - x_j) \Pi^h(x, dy)$$

# Convergence to SDE

By setting  $\mu^h = Nh$  we obtain:

$$b_i^h(x) = \frac{1}{N} \sum_{j=1}^N p_{ij}(x) (x_j - x_i),$$
$$a_{ii}^h(x) = h \left( \sum_{j=1}^N p_{ij}(x) (x_j - x_i)^2 \right).$$

# Convergence to ODE

By setting  $\mu^h = Nh$  we obtain:

$$b_i^h(x) = \frac{1}{N} \sum_{j=1}^N p_{ij}(x) (x_j - x_i),$$
$$a_{ii}^h(x) = h \left( \sum_{j=1}^N p_{ij}(x) (x_j - x_i)^2 \right).$$

Using some results from Durrett's Stochastic Calculus, we have that **as  $h \rightarrow 0$  the ABM converges** in probability to the solution of

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_{j=1}^N p_{ij}(x) (x_j - x_i)$$

# Is this the ODE model?

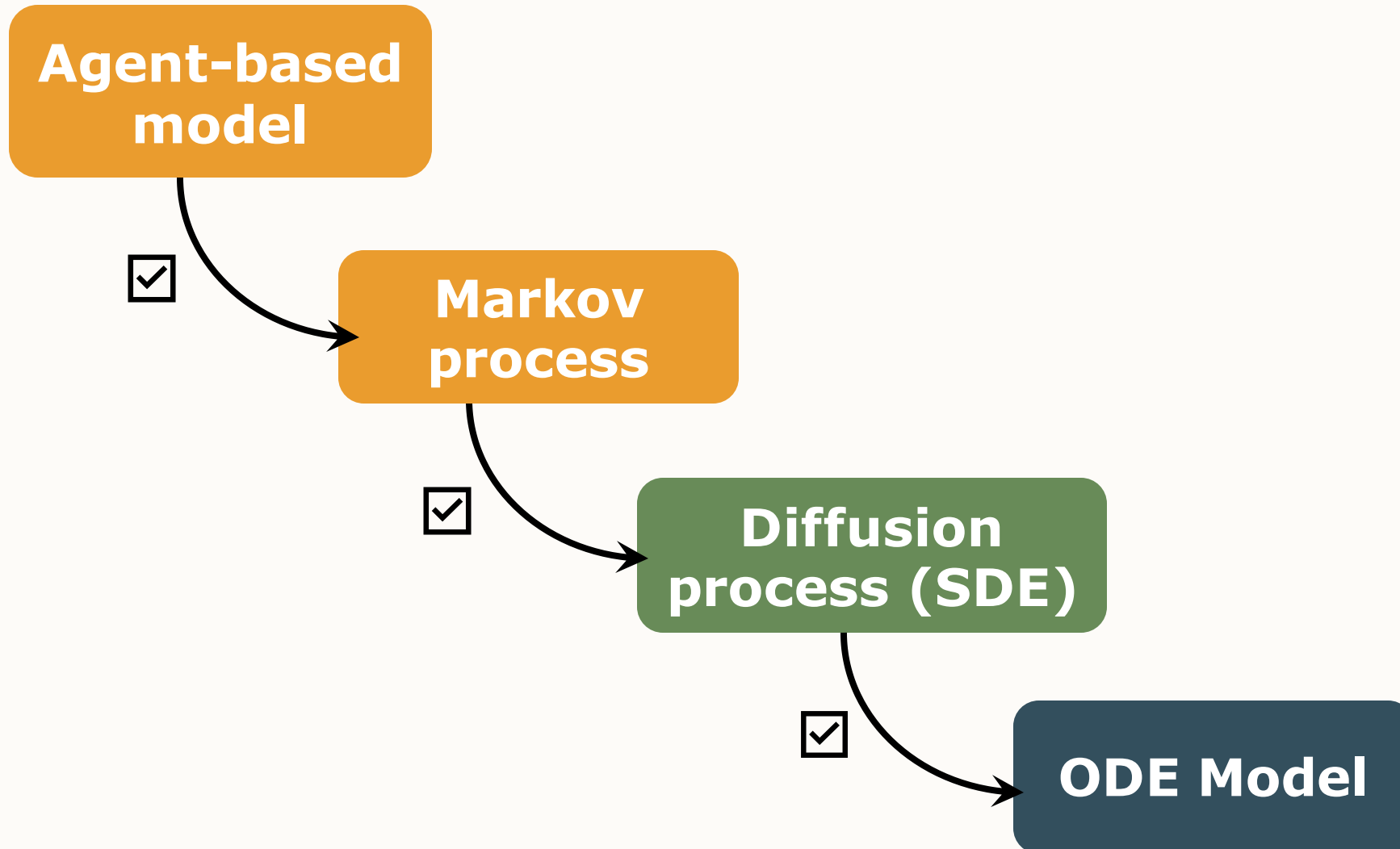
$$\frac{dx_i}{dt} = \frac{1}{N} \sum_{j=1}^N p_{ij}(x) (x_j - x_i)$$

$$p_{ij}(x) = \phi(|x_j - x_i|)$$

The interaction function is precisely the **probability** of an interaction occurring.

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_{j=1}^N \phi(|x_j - x_i|) (x_j - x_i)$$

# Link established!

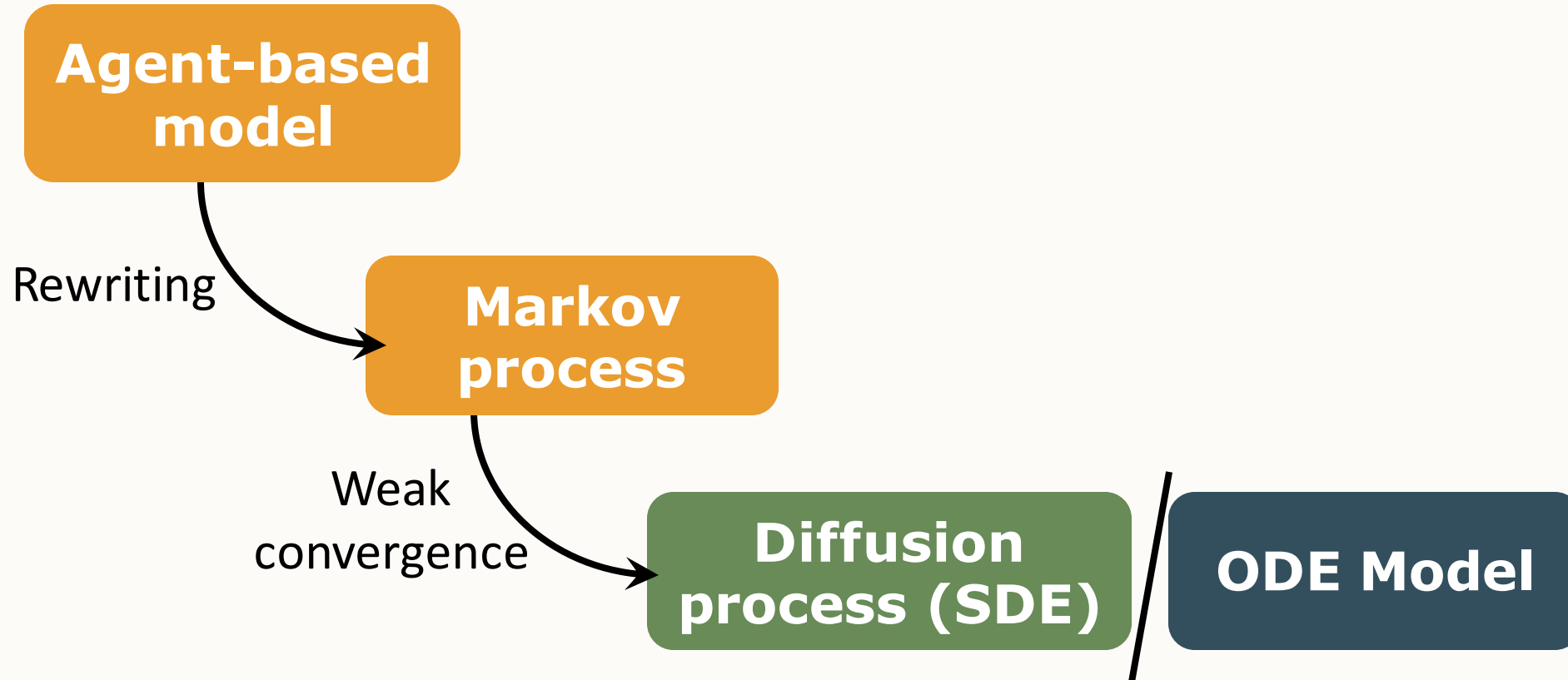


# What does this mean?

## Result:

1. The ODE model can be obtained by rescaling the timestep  $h$  and update distance  $\mu^h = Nh$  of the ABM.
2. This means the ODE model approximates **small but frequent pairwise interactions**, so is a realistic model if these assumptions hold.

# Following the link





# External noise

Change the update rule by adding a new noise term  $\xi^h$  with mean zero and variance that decreases with  $h$ .

$$x_i(t+h) = \begin{cases} x_i(t) + \mu^h (x_j(t) - x_i(t)) + \xi^h & \text{with probability } p_{ij}(x) \\ x_i(t) + \xi^h & \text{with probability } 1 - p_{ij}(x). \end{cases}$$

This noise translates directly in the limiting model

$$dX_i = \underbrace{\frac{1}{N} \sum_{j=1}^N p_{ij}(X) (X_j - X_i) dt}_{\text{Same drift as ODE model}} + \underbrace{\sqrt{\frac{1}{N} \lim_{h \rightarrow 0} \left( \frac{\mathbb{E}[(\xi^h)^2]}{h} \right)}}_{\text{New diffusion term}} d\beta_i$$

# Noisy update distance

Replace the fixed update distance with a random variable

$$x_i(t+h) = \begin{cases} x_i(t) + \nu^h (x_j(t) - x_i(t)) & \text{with probability } p_{ij}(x) \\ x_i(t) & \text{with probability } 1 - p_{ij}(x). \end{cases}$$

Again, this noise translates into the limiting model

$$dX_i = \frac{1}{N} \sum_{j=1}^N p_{ij}(X) (X_j - X_i) dt + \sqrt{\frac{m_2(\nu)}{N^2} \left( \sum_{j=1}^N p_{ij}(X) (X_j - X_i)^2 \right)} d\beta_i$$

# Ambiguity noise

Assume that the interaction probability is given by

$$p_{ij}(x) = \phi(|x_j - x_i|)$$

and updates are given by

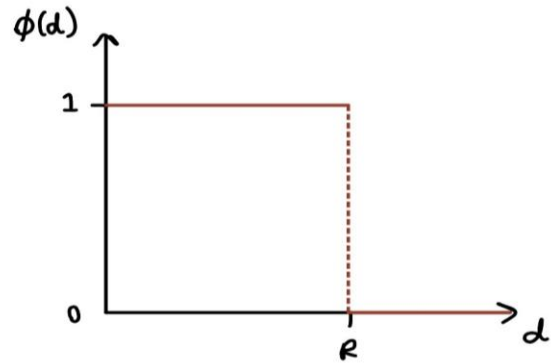
$$x_i(t+h) = \begin{cases} x_i(t) + \mu^h (\omega_j(t) - x_i(t)) & \text{with probability } \phi(|\omega_j - x_i|) \\ x_i(t) & \text{with probability } 1 - \phi(|\omega_j - x_i|). \end{cases}$$

with  $\omega_j = x_j + \eta^h$ .

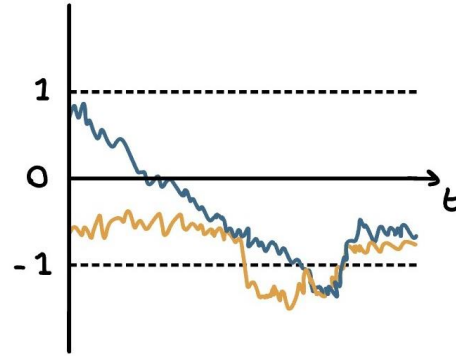
Then we obtain the same ODE as before!

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_{j=1}^N p_{ij}(x) (x_j - x_i)$$

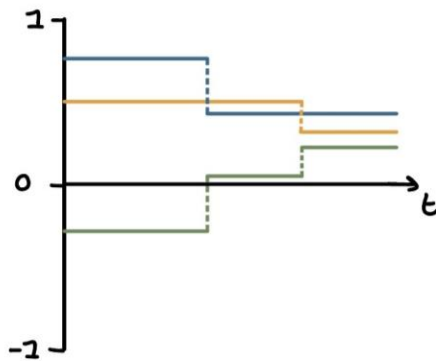
# Limitations



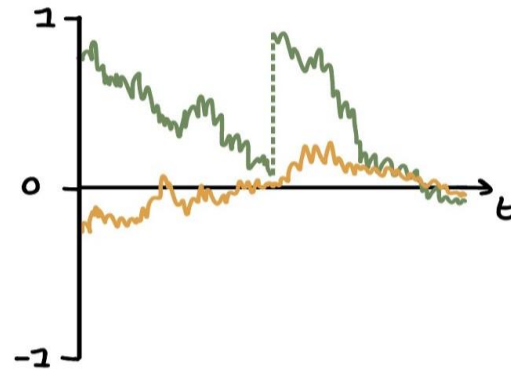
Discontinuous  $\phi$



Boundary conditions



Invalid assumptions



Additional features in ABM

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Engineering and  
Physical Sciences  
Research Council

