# On evolving network models and their influence on opinion formation

Andrew Nugent, Susana Gomes, Marie-Therese Wolfram a.nugent@warwick.ac.uk In this talk I will introduce a novel model of opinion dynamics that couples an opinion formation model with a general interaction function to a coevolving social network in which individuals build relationships through continued meaningful interaction.





**Axelrod's Puzzle:** "If people tend to become more alike in their beliefs, attitudes, and behaviour when they interact, why do not all such differences eventually disappear?"



Bounded confidence set:  $I(x,i) = \{ j : |x_i - x_j| < R \}$ 

Bounded confidence dynamics:

$$\frac{dx_i}{dt} = \frac{1}{|I(x,i)|} \sum_{j \in I(x,i)} (x_j - x_i)$$



Bounded confidence dynamics:

$$\frac{dx_i}{dt} = \frac{1}{|I(x,i)|} \sum_{j \in I(x,i)} (x_j - x_i)$$

Define the interaction function:

$$\phi_R(|x_i - x_j|) = \begin{cases} 1 \text{ if } |x_i - x_j| < R\\ 0 \text{ if } |x_i - x_j| \ge R \end{cases}$$

Bounded confidence dynamics:

$$\frac{dx_i}{dt} = \frac{\sum_j \phi_R(|x_i - x_j|)(x_j - x_i)}{\sum_j \phi_R(|x_i - x_j|)}$$

Bounded confidence dynamics:  

$$\frac{dx_i}{dt} = \frac{\sum_j \phi_R(|x_i - x_j|)(x_j - x_i)}{\sum_j \phi_R(|x_i - x_j|)}$$
Simplify the normalisation  
Bounded confidence dynamics:  

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_j \phi_R(|x_i - x_j|)(x_j - x_i)$$



$$\frac{dx_i}{dt} = \frac{1}{N} \sum_j \phi_R(|x_i - x_j|)(x_j - x_i)$$

Define a general interaction function:  $\phi(|x_i - x_j|) : [0,2] \rightarrow [0,1]$ 

General opinion dynamics:

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

Bounded confidence dynamics:  

$$\frac{dx_i}{dt} = \frac{1}{|I(x,i)|} \sum_{j \in I(x,i)} (x_j - x_i)$$

General opinion dynamics:  $\frac{dx_i}{dt} = \frac{1}{N} \sum_j \phi(|x_i - x_j|)(x_j - x_i)$ 

### What does $\phi$ now represent?

- The attention/value you give somebody's opinion?
- How much an opinion influences you?
- How much dissonance/discomfort the difference in opinion creates?
- Some unspecified mix of these effects?



Example interaction functions:  $\phi_1(r) = \begin{cases} 1 \text{ if } r \le 0.3 \\ 0 \text{ if } r \ge 0.3 \end{cases}, \quad \phi_2(r) = e^{-6r}, \ \phi_3(r) = \frac{8}{5} \left( r - \frac{1}{2} \right)^2 (r+1)(r-2)^2 \end{cases}$ 



Example interaction functions:  $\phi_1(r) = \begin{cases} 1 \text{ if } r \le 0.3 \\ 0 \text{ if } r \ge 0.3 \end{cases}, \quad \phi_2(r) = e^{-6r}, \ \phi_3(r) = \frac{8}{5} \left( r - \frac{1}{2} \right)^2 (r+1)(r-2)^2 \end{cases}$  **Definition:** The **opinion diameter** is given by:

 $D(t) = \max_{i,j} |x_j(t) - x_i(t)|.$ 

**Definition:** The population reaches **consensus** if:

 $\lim_{t\to\infty}D(t)=0.$ 

General opinion dynamics:

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

**Proposition:**  $x_i(t) \in [-1,1]$  for all  $t \ge 0$ . Additionally, D(t) converges to some value in [0,2] as  $t \to \infty$ .

**Proposition**: For any  $\epsilon > 0$  there exists a time  $t^*$  at which, for all pairs of individuals *i* and *j* 

$$\phi(|x_j(t^*) - x_i(t^*)|) |x_j(t^*) - x_i(t^*)|^2 < \epsilon.$$

**<u>Proposition</u>**: If there exists a constant c > 0 such that  $\phi(r) > c$  for all  $r \in [0,2]$  then **consensus is guaranteed** for any x(0).



So far...

- Seen some history of opinion dynamics
- Constructed a general model
- Observed both consensus and polarisation.



General opinion dynamics:  

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_j \phi(|x_i - x_j|)(x_j - x_i)$$
Introduce a network: *w*  
Network opinion dynamics:  

$$\frac{dx_i}{dt} = \frac{1}{N} \sum_j w_{ij} \phi(|x_i - x_j|)(x_j - x_i)$$

Network opinion dynamics:  $\frac{dx_i}{dt} = \frac{1}{N} \sum_{i} w_{ij} \phi(|x_i - x_j|)(x_j - x_i)$ Account for network in normalisation  $k_i = \sum_i w_{ij}$ Network opinion dynamics:  $\frac{dx_i}{dt} = \frac{1}{k_i} \sum_{i} w_{ij} \phi(|x_i - x_j|)(x_j - x_i)$ 

General opinion dynamics:

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

Network opinion dynamics:  $\frac{dx_i}{dt} = \frac{1}{k_i} \sum_j w_{ij} \phi(|x_i - x_j|)(x_j - x_i)$ 

### What does w represent?

- Spatial constraints?
- To indicate expertise?
- Social relationships (e.g. trust, confidence)?





**Definition:** The opinion diameter is given by:

 $D(t) = \max_{i,j} |x_j(t) - x_i(t)|.$ 

**Definition:** The population reaches consensus if:

 $\lim_{t\to\infty}D(t)=0.$ 

Network opinion dynamics:  $\frac{dx_i}{dt} = \frac{1}{k_i} \sum_j w_{ij} \phi(|x_i - x_j|)(x_j - x_i)$ 

**Proposition:**  $x_i(t) \in [-1,1]$  for all  $t \ge 0$ . Additionally, D(t) converges to some value in [0,2] as  $t \to \infty$ .

**Proposition**: For any  $\epsilon > 0$  there exists a time  $t^*$  at which, for all pairs of individuals *i* and *j* 

$$w_{ij} \phi(|x_j(t^*) - x_i(t^*)|) |x_j(t^*) - x_i(t^*)|^2 < \epsilon.$$

<u>**Proposition:**</u> If *w* is connected and there exists a constant c > 0 such that  $\phi(r) > c$  for all  $r \in [0,2]$  then consensus is guaranteed for any x(0).

Bounded confidence on a network:  

$$\frac{dx_i}{dt} = \frac{1}{k_i} \sum_j w_{ij} \phi_R(|x_i - x_j|)(x_j - x_i)$$

#### Networks:

- Using Erdos-Renyi random networks with edge probability p.
- The expected number of connections for each node is *Np*.

Order parameter:

$$Q = \frac{1}{N^2} \sum_{i,j} \phi_R(|x_i - x_j|)$$

## Case Study: Bounded Confidence













#### So far...

- Constructed a general network model
- Extended analytic results to include a network.
- Investigated the complex impact of R and p.





$$\frac{dx_i}{dt} = \frac{1}{k_i} \sum_{j=1}^N w_{ij} \phi(|x_j - x_i|) (x_j - x_i)$$
$$\frac{dw_{ij}}{dt} = \phi(|x_j - x_i|) \quad \text{Growth function} \quad -\left(1 - \phi(|x_j - x_i|)\right) \quad \text{Decay function}$$

Memory weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|)(1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij}$$

Logistic weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|) w_{ij} (1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij} (1 - w_{ij})$$

Friend-of-a-friend (FOAF) weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|) (w_{ij} + \lambda(W^2)_{ij}) (1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij}$$

Memory weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|)(1 - w_{ij}) - (1 - \phi(|x_i - x_j|))w_{ij}$$
  
=  $\phi(|x_i - x_j|) - w_{ij}$   
 $w_{ij}(t) = e^{-t}w_{ij}(0) + \int_0^t e^{s-t}\phi(|x_j(s) - x_i(s)|) ds$ 

Logistic weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|) w_{ij} (1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij} (1 - w_{ij})$$
$$= (2\phi(|x_i - x_j|) - 1) w_{ij} (1 - w_{ij})$$

Friend-of-a-friend (FOAF) weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|) (w_{ij} + \lambda (W^2)_{ij}) (1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij}$$

Memory weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|)(1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij}$$
  
=  $\phi(|x_i - x_j|) - w_{ij}$ 

Logistic weight dynamics:

$$\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|) w_{ij} (1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij} (1 - w_{ij})$$
$$= (2\phi(|x_i - x_j|) - 1) w_{ij} (1 - w_{ij})$$

Friend-of-a-friend (FOAF) weight dynamics:  $\frac{dw_{ij}}{dt} = \phi(|x_i - x_j|) (w_{ij} + \lambda (W^2)_{ij}) (1 - w_{ij}) - (1 - \phi(|x_i - x_j|)) w_{ij}$ 





### Logistic network dynamics

Memory network dynamics

Exponential interaction function:  $\phi^{\alpha}(|x_i - x_j|) = e^{-\alpha r |x_i - x_j|}$ 

## Case Study: Exponential interaction





Opinion dynamics models capture consensus, polarisation and fragmentation.

Introducing a network creates a complex pattern of behaviours.

A new model where the interaction function balances growth and decay of edge weights.

> Network dynamics can both help create consensus and entrench polarised views.

# On evolving network models and their influence on opinion formation

Andrew Nugent, Susana Gomes, Marie-Therese Wolfram a.nugent@warwick.ac.uk

