# **Detecting Zealots in Social Networks** A Spatial Autoregressive (SAR) Model Approach

**Introductory Econometrics Final Presentation** 

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# Outlines

- Opinion Dynamics and Social Network
- The Interference of Zealots
- Conventional Deffuant model: Test Statistics Adaptive Network: Spatial Autoregressive model
- Toward Applied Microeconomic Theory Studies

## **Opinion Dynamics** Social Network

- Network = Nodes + Edges
- Nodes: social actors
- Edges: connections



# **Opinion Dynamics**

- Node attributes:
  - opinion: -1~1
- Nodes will exchange their opinion



## **Opinion Dynamics Deffuant model**

- For each time, an edge is chosen randomly
- If the difference of their opinion < C :

• 
$$o_1 \leftarrow o_1 + \alpha(o_2 - o_1)$$

• 
$$o_2 \leftarrow o_2 + \alpha(o_1 - o_2)$$

## **Opinion Dynamics Deffuant model with zealot**

- For each time, an edge is chosen randomly
- If the difference of their opinion < C :

• 
$$o_1 \leftarrow o_1 + \alpha(o_2 - o_1) \cdot z_1$$

• 
$$o_2 \leftarrow o_2 + \alpha(o_1 - o_2) \cdot z_2$$

• where  $z_i = 0$  if *i* is zealot, otherwise 1

#### **The Interference of Zealots** Conservation without zealots

• 
$$o_1^{t+1} = o_1^t + \alpha (o_2^t - o_1^t)$$
  
•  $o_2^{t+1} = o_2^t + \alpha (o_1^t - o_2^t)$   
•  $o_1^{t+1} + o_2^{t+1} = o_1^t + o_2^t$   
•  $\sum o_i^{t+1} = \sum o_i^t$ 

#### The Interference of Zealots Conservation broke by zealots

• 
$$o_1^{t+1} = o_1^t$$
 (zealot)

• 
$$o_2^{t+1} = o_2^t + \alpha(o_1^t - o_2^t)$$

• 
$$o_1^{t+1} + o_2^{t+1} = o_1^t + o_2^t + \alpha(o_1^t - o_2^t)$$

• 
$$\sum o_i^{t+1} = \sum o_i^t + \alpha (o_1^t - o_2^t)$$

Mean opinion moves towards *o*<sub>1</sub>





## **Test Statistics Motivation**

- Population mean will remain the same if there is no zealot
- Population mean will move toward a value if there is zealots
- Suppose we
  - Sample periodically
  - Calculate sample mean
  - Run linear regression  $\bar{o}_t \sim t$  and get  $R^2$
- We get to distinguish the two cases

#### **Test Statistics** Monte Carlo

- Repeat 100 times:
  - Simulate opinion dynamics (with (10\*edge number) iterations)
  - Sample opinions with same / different people for 25 panel waves
  - Calculate the  $R^2$  of mean opinions time evolution

#### **Conventional Deffuant model: Test Statistics Result:** same people



 $R^2$  Without Zealot



 $R^2$  With Zealot (o = 0.3)



#### **Conventional Deffuant model: Test Statistics Result: different people**



 $R^2$  Without Zealot



 $R^2$  With Zealot (o = 0.3)



# Adaptive Network

- People are smart (maybe not), and they choose whom to be friends
- In this study, they make decision based on *Similarity*
- We consider opinion similarity, which is also known as the social learning (DeGroot, 1974)

\* Generalization is possible (See Appendix)



Credit: iStock







# Single Agent (Ego)



## **Adaptive Network Spatial Autoregressive Model**

## $\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}$

- y is the response variable
- $\rho$  is the spatial lag coefficient
- W is the adjacency matrix of the network
- X is the exogenous variables
- $\beta$  is the coefficient of exogenous effects
- $\epsilon$  is the error term

## Adaptive Network Spatial Autoregressive Model

# $\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}$

- In the past, linear-in-means models are used to study the peer effects (Manski, 1993)
- However, it can not deal with endogenous effects
  Hence, we use MLE methods proposed by Lee et al (2004). See
- Hence, we use MLE methods p Appendix

## **Adaptive Network SAR Model on Opinion Dynamics**

## $\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}$

- y is the opinions of agents
- $\mathbf{X}_1$  is the degree of nodes (baseline)
- **X**<sub>2</sub> is the clustering coefficients
- We collect multiple panel waves from MCMC

\* We mostly care about  $\rho$  and  $\beta_2$ 

# $\mathbf{y} = \rho \mathbf{W} \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + \boldsymbol{\epsilon}$





#### Adaptive Network Population Analysis – Goodness of Model Fitting



10 zealot with  $o(z_i) = 0.9, \forall i \in Z$ 

#### Adaptive Network Population Analysis – Peer Effects





#### **Adaptive Network** Population Analysis – Clustering Effects



10 zealot with  $o(z_i) = 0.9, \forall i \in \mathbb{Z}$ 



## Adaptive Network Snowball Sampling







### **Adaptive Network Snowball Sampling Analysis – Goodness of Model Fitting**





10 zealot with  $o(z_i) = 0.9, \forall i \in Z$ 

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#### **Adaptive Network Snowball Sampling Analysis – Peer Effects**



10 zealot with  $o(z_i) = 0.9, \forall i \in Z$ 



## **Adaptive Network** Population Analysis – Inference

- SAR model could infer peer effects in opinion dynamics
- Comparison between spatial lag coefficients suggests that zealots induce rewiring and social learning
- There is no significance on clustering effects
- Social learning is observed on the network's global topology

#### Don't be fooled by your ego and belief. Hold your faith with a good personality if you want to change something.

## **Toward Applied Microeconomic Theory Studies Extensions in Theoretical & Empirical Studies**

#### Microeconomic initiated concepts

- 1. Mechanism design (Renou, 2012)
- 2. Bounded rationality (Mueller-Frank, 2013)
- 3. Collective behavior (Acemoglu, 2014)

#### **Empirical Studies**

- 1. Social preferences (Hsieh, 2018)
- 2. Altruistic TU game strategy (Leider, 2009)

#### **Statistical/Econometric Approaches**

- 1. Stochastic Actor Based model (Snijder, 2011)
- 2. Unbiased Network Sampling (Hsieh, 2022)



## **Toward Applied Microeconomic Theory Studies** My work – An Advertisement

- Testing altruism in the core of social movements On the egalitarian coalition-strategies
- On the biasness of the estimation for social behavior in dynamic networks

#### Share your ideas a 陳柏安 (Bo-An Che 陳立凡 (Li-Fan Che

- Share your ideas and suggestions with us!
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# References

- DeGroot, (1974), Journal of the American Statistical Association, 69(345), 118-121.
- Kan et al., (2023), Journal of Complex Networks, Volume 11, Issue 1
- Manski, (1993), The Review of Economic Studies, Vol. 60, pp. 531–542.
- Lee, (2004), Econometrica, Vol. 72, pp. 1899–1925.
- Renou & Tomala, T. (2012), *Theoretical Economics*, 7: 489-533.
- Mueller-Frank, M. (2013), *Theoretical Economics*, 8: 1-40.
- Acemoglu et al, (2014), *Theoretical Economics*, 9: 41-97.
- Hsieh, C.-S. and van Kippersluis, H. (2018), *Quantitative Economics, 9: 825-863.*
- Snijder et al, (2011), Social Networks, Volume 32, Issue 1, January 2010, Pages 44-60
- Hsieh et al, (2022), "Non-randomly Sample Networks: Biases and Corrections" (Revision requested by Journal of *Econometrics*)

Leider et al, (2009), The Quarterly Journal of Economics, Volume 124, Issue 4, November 2009, Pages 1815–1851

# **Appendix: MLE for SAR**

# $log(ML)_{SAR} = -\frac{N}{2}log(2\pi) - \frac{1}{2}log(det(\mathbf{V})) + log(det(\mathbf{S})) - \frac{1}{2}\epsilon^{\mathsf{T}}\mathbf{V}^{-1}\epsilon$

- N is the number of nodes (agents)
- V is the covariance matrix
- S is spatial correlation matrix  $\mathbf{I}_{N \times N} \rho \mathbf{W}$

# **Appendix: Clustering Coefficient**

- T(u) is the number of triangles through node u
- deg(u) is the degree of u

 $c_u = \frac{2T(u)}{deg(u)(deg(u) - 1)}$ 

NetworkX Documentation

# **Appendix: Pseudo-code for Adaptive DW model**

Algorithm 1 Pseudocode for our Adaptive DW Model

**parameters:** N, p, M, K,  $\alpha$ ,  $\beta$ , C 1:  $t \leftarrow 0$ ;  $G \leftarrow G(N, p)$ 2: for  $i \in G$ .nodes() do  $x_i(0) \leftarrow \text{Unif}[0,1]$ 3: 4: end for 5: while (time t < bail-out time) and (sum of the magnitudes of the opinion changes < tol for fewer than 100 consecutive steps) do  $E_d^{\beta}(t) \leftarrow \emptyset$  [initialize set of discordant edges] 6: for (i, j) in the set of edges E(t) do 7: if  $|x_i(t) - x_j(t)| < \beta$  then  $E_d^\beta(t) \leftarrow E_d^\beta(t) \cup \{(i, j)\}$ 8: end if 9: end for 10: if  $|E_d^{\beta}(t)| > M$  then select *M* edges uniformly at random from  $E_d^{\beta}(t)$ 11: else select all edges from  $E_{d}^{\beta}(t)$ 12: end if 13: for each discordant edge (i, j) do 14: dissolve and remove the edge from the edge set E(t)15: select node *i* or *j* with equal probability 16: compute probabilities to rewire to other nodes using (3.1)17: randomly pick another node using the computed rewiring probabilities 18: connect the node to the previously selected node with an edge; add the new edge to E(t)19: end for 20: select K edges uniformly at random from E(t)21: for each selected edge (i, j) do 22: if  $|x_i(t) - x_i(t)| \leq C$  then update the opinions of the nodes using (3.2) 23:

[see the main text for further discussion]

end if 25:

end for 26:

24:

compute the sum of the magnitudes of the opinion changes 27:

```
t \leftarrow t + \Delta t
28:
```

29: end while

Parameters:  $x_i(o) \in (-1,1)$ G: Erdős–Rényi Graph ~ G(1000, 0.1) N: 1000 p: 0.1 M: 50 K: 30  $\alpha$ : 0.6  $\beta$ : 0.6 C: 0.6



