

## Indirect influence in social networks as an induced percolation phenomenon

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## Content

- Motivation
- Methods
- Results
- Take-away message

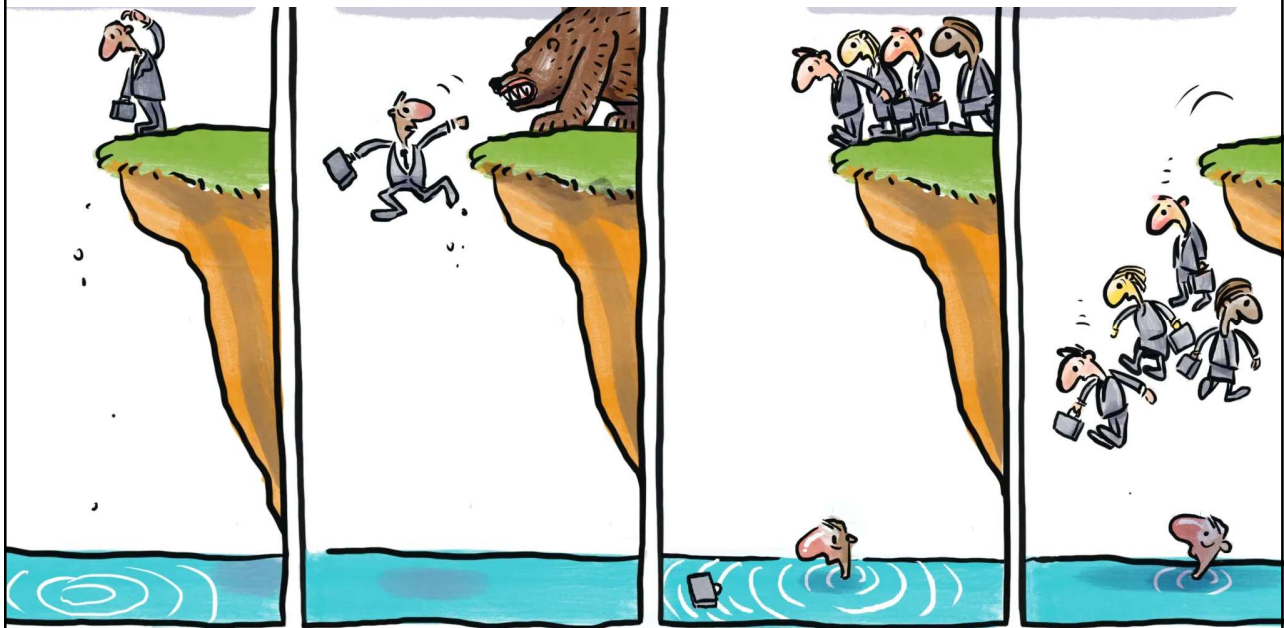
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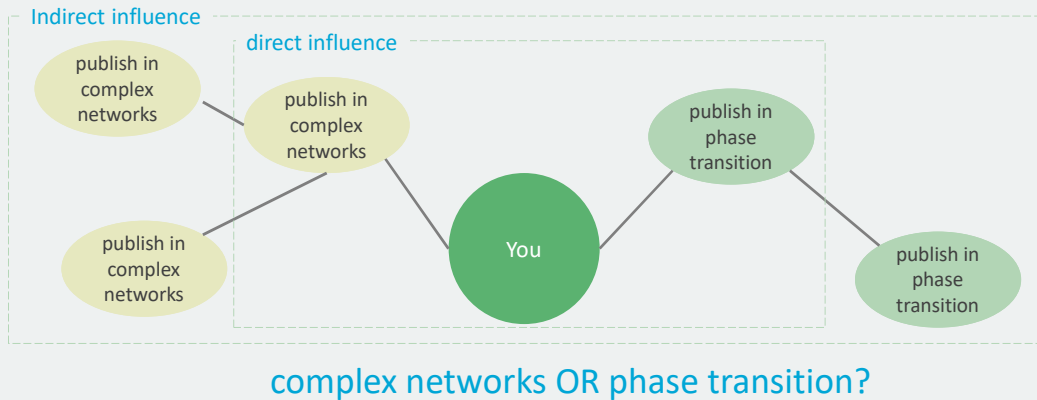
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## Motivation- behaviors can be contagious in social networks



## Motivation- behaviors can be contagious in social networks

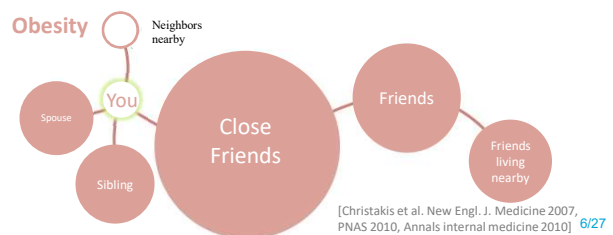
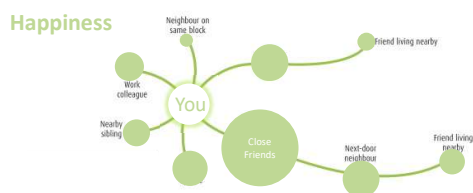
### Publishing behavior in collaboration networks



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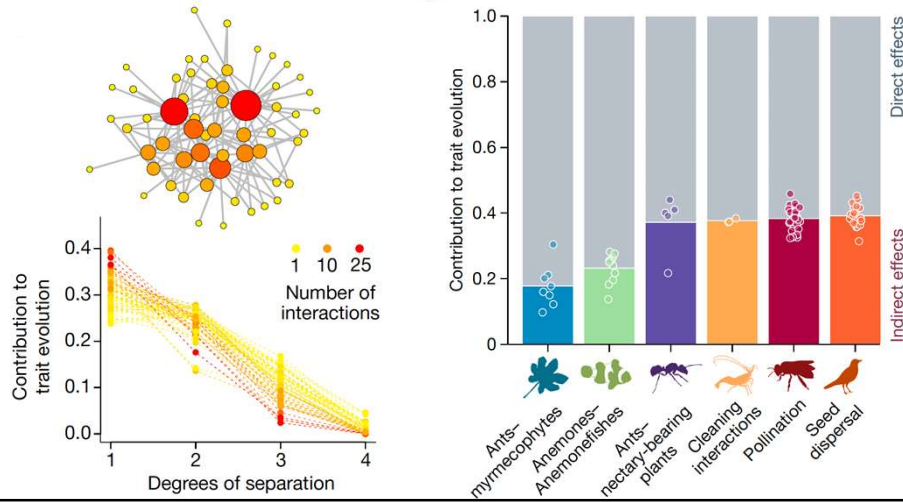
## Motivation- Indirect influence in behavior contagion

- Indirect influence in behavior contagion from social experiments
  - Obesity experiment lasting 32 years
    - person-to-person spread of obesity
    - extended to three degrees of separation
  - Repeatedly found in behaviors of happiness, smoking, drug, alcohol, loneliness, among others.



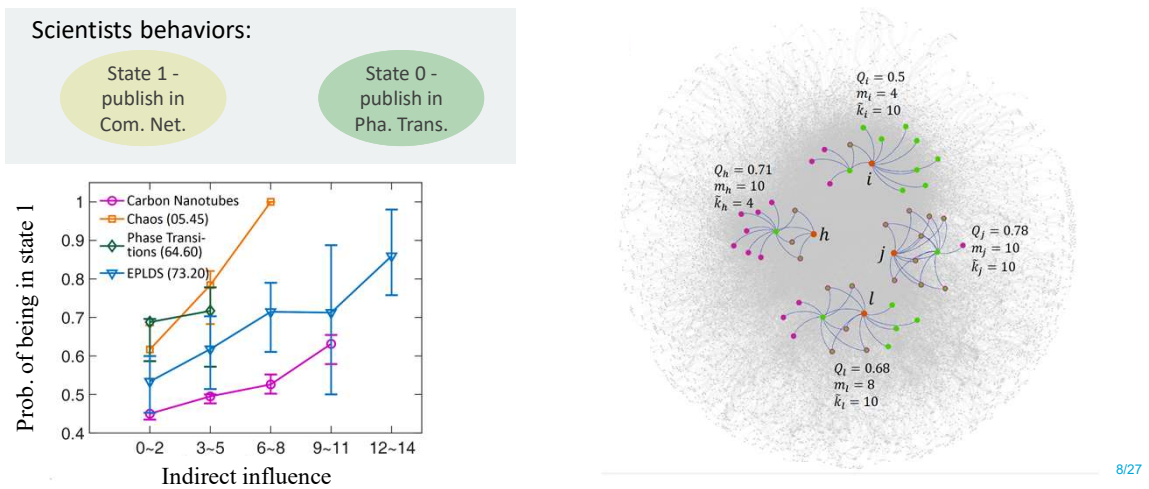
## Motivation- Indirect influence in behavior contagion

- Indirect influence observed in ecological trait evolution.



## Motivation- Indirect influence in behavior contagion

- Indirect influence observed in scientific collaboration



## Research question

What are the potential underpinning mechanisms for indirect influence in behavior contagion,

so that we can propose models to mimic the contagion process?

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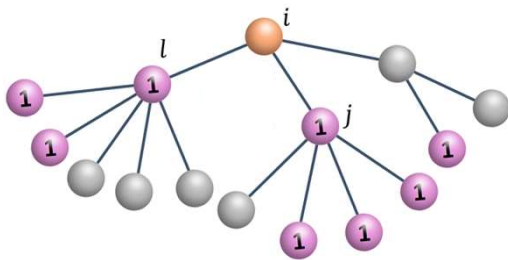
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## Indirect influence as an induced percolation

- **Model of Induced percolation:**



Induced index  $m_i$  :

$m_i =$  { Max indirect (second) neighbors in state 1  
of those  
Direct neighbors in state 1

$m_i = 3$

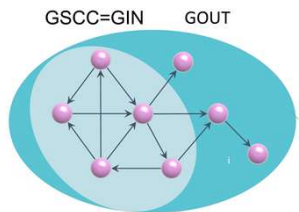
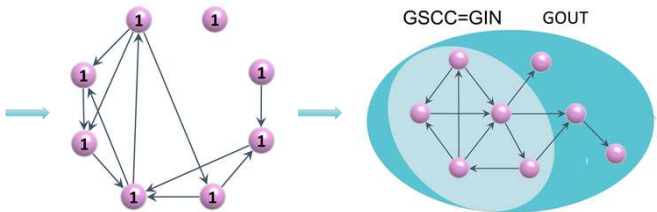
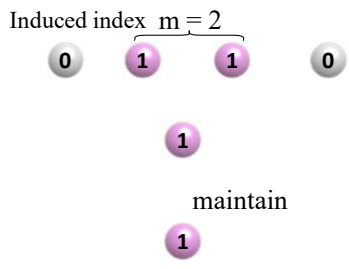
$k_i = 2, d_i = 6$

Direct influence as comparison  
 $k_i$ : directed neighbors in state 1  
 $d_i$ : second neighbors in state 1

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## Indirect influence as an induced percolation

- **Model of Induced percolation:**



Order parameter GOUT:  
 corresponds to the largest  
 spreading coverage.

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## Indirect influence as an induced percolation

- Model of Induced percolation:**

Induced index  $m = 2$

maintain

$x$ : Prob. of starting node in state 1  
 $y$ : Prob. of an end node in state 1  
 $P_{\infty}$ : Order parameter GOUT

$$x = \sum_{k_{in}, k_{out}} \frac{k_{out} P(k_{in}, k_{out})}{\langle k \rangle} [1 - (1 - y)^{k_{in}}]$$

$$y = \sum_{k_{in}, k_{out}} \frac{k_{out} P(k_{in}, k_{out}) \sum_{s=m}^{k_{in}} \binom{k_{in}}{s} x^s (1-x)^{k_{in}-s}}{\langle k \rangle} [1 - (1 - \frac{y}{x})^s]$$

$$P_{\infty} = \sum_{k_{in}, k_{out}} P(k_{in}, k_{out}) [1 - (1 - y)^{k_{in}}]$$

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## Indirect influence as an induced percolation

- Model of Induced percolation:**

- Induced percolation on undirected networks

$\bar{y}_{\infty} = 1 - \bar{y}$

$\bar{l}_{\infty} = 1 - \bar{l}$

$\bar{y}_{\infty} = 1 - \bar{y}$

$\bar{a}_{\infty} = 1 - \bar{a}$

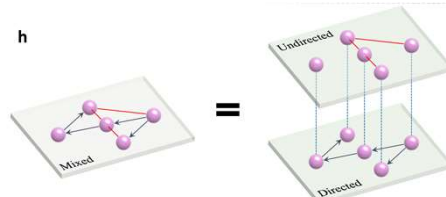
$\bar{y}_{\infty} = 1 - \bar{y}$

$\bar{a}_{\infty} = 1 - \bar{a}$

■  $k > m$   
 ●  $k \leq m$

- Induced percolation on mixed networks

Conditional probability	Link type	Conditional event	Occurring event	Relation
$\bar{y}$	Directed (j, l)	None	$j \rightarrow l$	$x = y + a$
$\bar{a}$			$j$ is active but $j \nrightarrow l$	
$\bar{x}$	Undirected (j, l)	None	$j \rightarrow l$	$\bar{x} = \bar{y} + \bar{a}$
$\bar{y}$			$j$ is active but $j \nrightarrow l$	
$\bar{a}$	Directed (j, l)	None	$(j) j \rightarrow l$	$\bar{x}_{\infty} = \bar{y}_{\infty} + \bar{a}_{\infty}$
$\bar{x}_{\infty}$			$(j) j$ is active	
$\bar{y}_{\infty}$	Undirected (j, l)	None	$l \rightarrow j$	and (i) l connects to GOUT via j
$\bar{a}_{\infty}$			$(j) j \rightarrow l$	
$\bar{x}_{\infty}$	Undirected (j, l)	None	$l \rightarrow j$	$\bar{x}_{\infty} = \bar{y}_{\infty} + \bar{a}_{\infty}$
$\bar{y}_{\infty}$			$(j) j \rightarrow l$	
$\bar{a}_{\infty}$	Undirected (j, l)	None	$l \rightarrow j$	$\bar{x}_{\infty} = \bar{y}_{\infty} + \bar{a}_{\infty}$
$\bar{x}_{\infty}$			$(j) j$ is active	



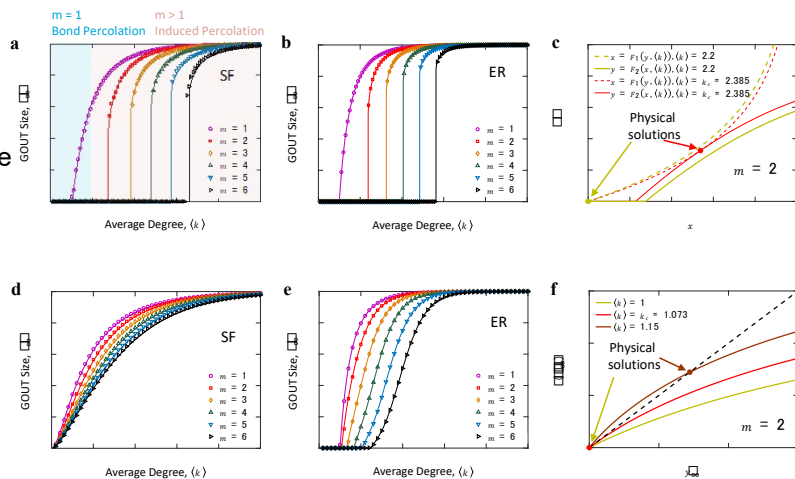
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# Rich critical behaviors induced by indirect influence

- Order parameter GOUT Size on directed nets
  - $\langle k \rangle$ : average degree
  - $m$ : induced index
- GOUT on undirected nets:



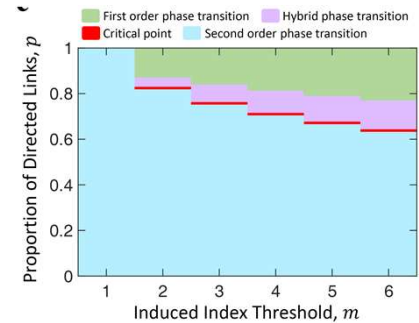
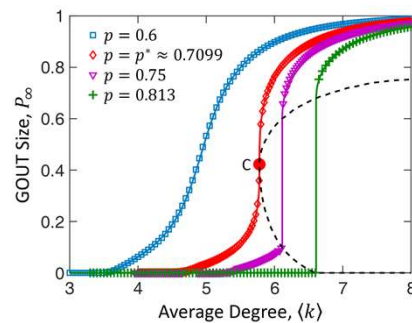
J Xie, X Wang, L Feng, JH Zhao, Y Moreno, Y Hu, Induced Percolation on Networked Systems, PNAS, 119(9), 2022.

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## Rich critical behaviors induced by indirect influence

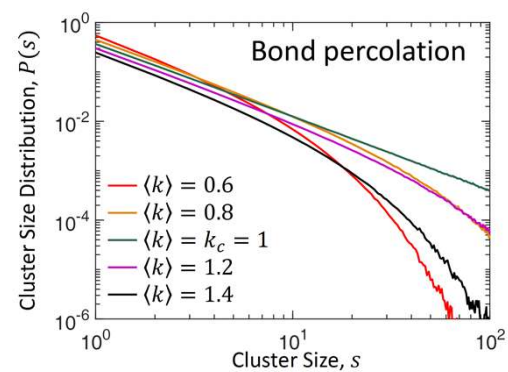
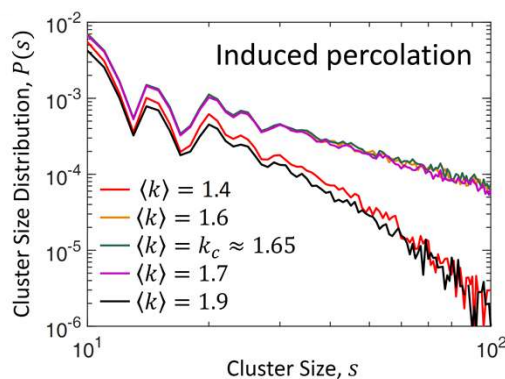
- GOUT on mixed nets:
  - $\langle k \rangle$ : average degree
  - $m$ : induced index
  - $p$ : proportion of directed links



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## Rich critical behaviors induced by indirect influence

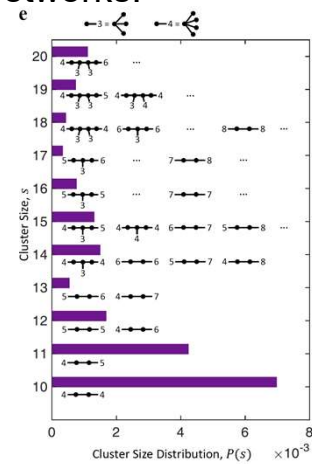
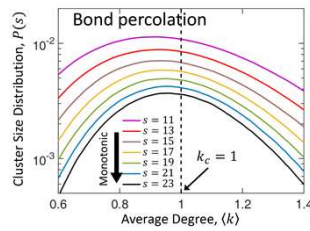
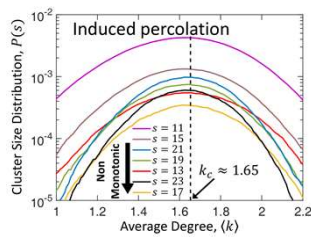
- Size distribution  $P(s)$  of small clusters at the critical point of induced percolation ( $m = 4$ ) on undirected networks.



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## Rich critical behaviors induced by indirect influence

- Size distribution  $P(s)$  of small clusters at the critical point of induced percolation ( $m = 4$ ) on undirected networks.



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## Take-away message

- Indirect influence in social networks as an induced percolation phenomenon
- Induced percolation leads to rich critical behaviors depending on a single network parameter.



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