

# Class 10: Thresholds, cascades, and predictability

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Sociology 204: Social Networks  
Princeton University

Wednesday, October 6, 2021



Summary:

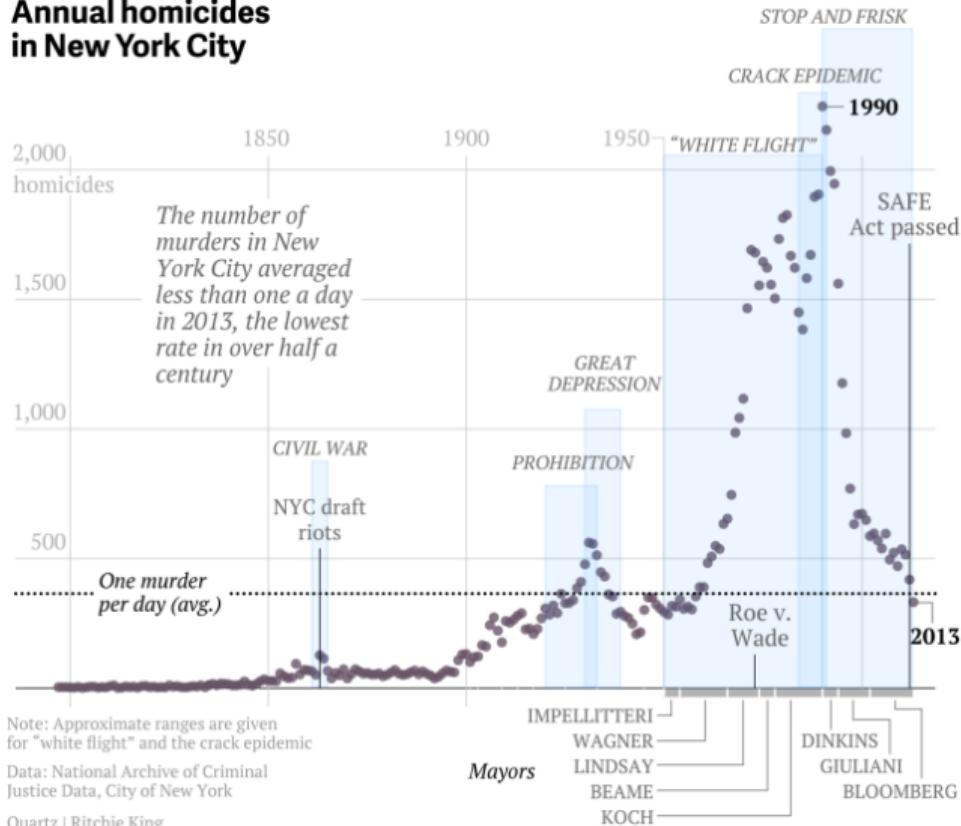
- ▶ many decisions are interdependent

## Summary:

- ▶ many decisions are interdependent
- ▶ when there are interdependent decisions, individual rationality can lead to collective irrationality

1. Gladwell, M. (1996). The tipping point. *The New Yorker*.
2. Watts, Chapter 8.
3. Watts, D.J. (2002). A simple model of global cascades on random networks. *Proceedings of the National Academy of Sciences*.

## Annual homicides in New York City

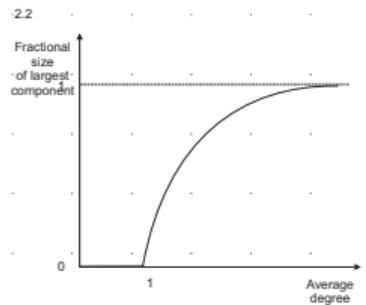


## Nonlinear change



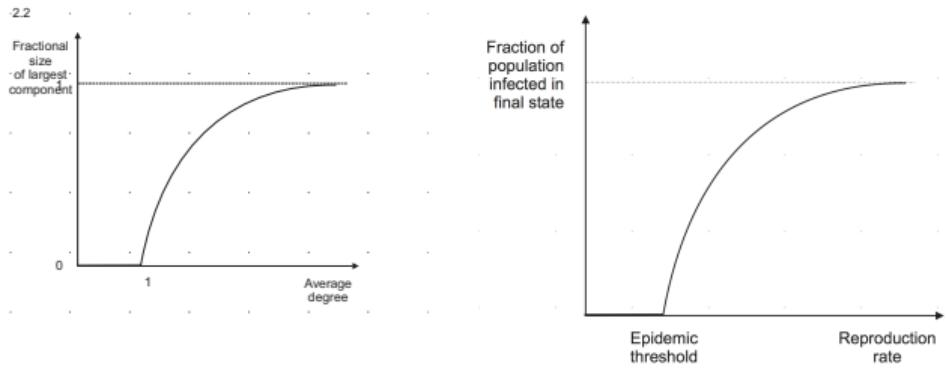
<http://www.davidmelamed.com/2013/07/15/user-testing-ketchup-bottles-leads-to-counter-intuitive-surge-in-profits/>

## Nonlinear change



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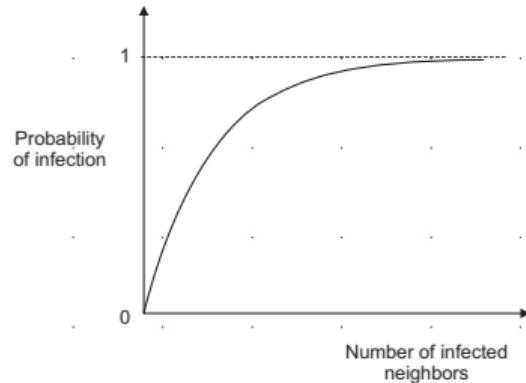
## Nonlinear change



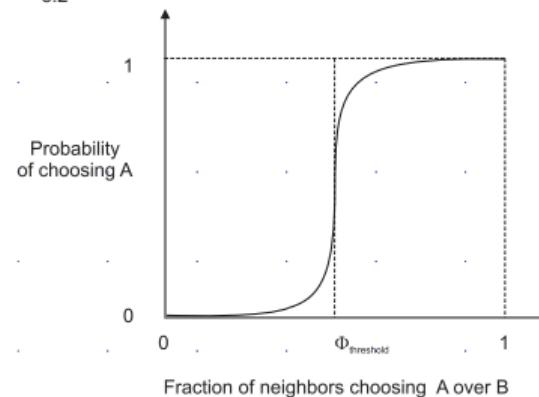
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“What if homicides, which we often causally refer to as an epidemic, actually *is* an epidemic, and moves through the populations the way that the flu bug does.” Malcolm Gladwell

8.1



8.2



(a) Probability of activation in disease spreading   (b) Probability of activation in social spreading

For more on why social decisions might involve thresholds, see Lopez-Pintado and Watts (2008) [Social Influence, Binary Decisions and Collective Dynamics](#)

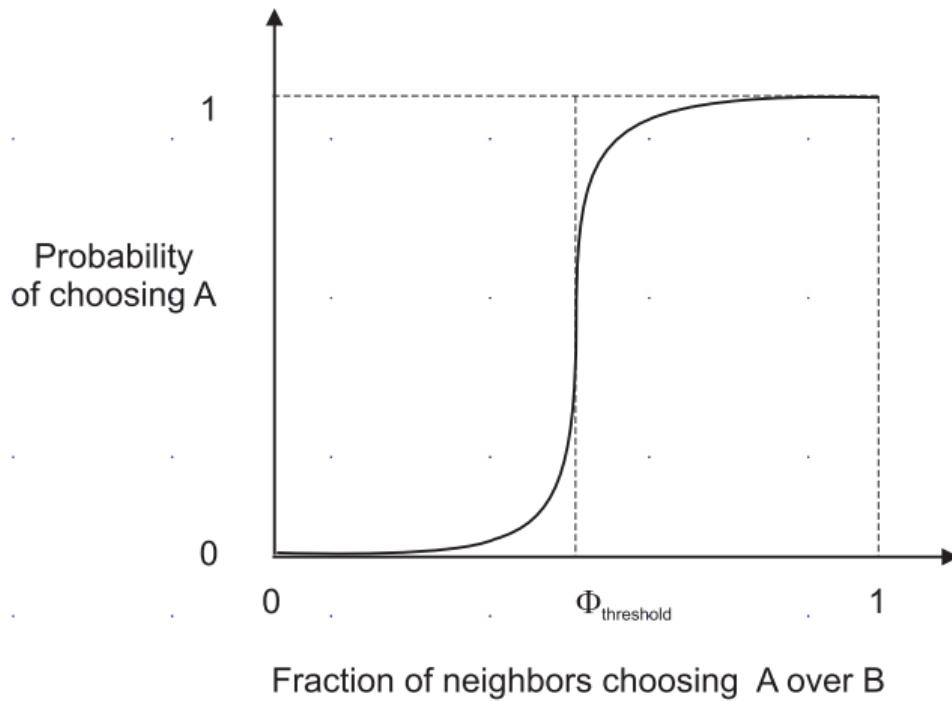
Differences between models of social contagion and biological contagion:

- ▶ social contacts are interdependent and disease contacts are independent

Differences between models of social contagion and biological contagion:

- ▶ social contacts are interdependent and disease contacts are independent
- ▶ social spreading on fraction of neighbors doing some behavior rather than absolute number: diseases depends on absolute number

8.2



Demo

Demo illustrates that

- ▶ hard to predict collective outcome from individual preferences

Demo illustrates that

- ▶ hard to predict collective outcome from individual preferences
- ▶ hard to infer individual preferences from collective outcomes

For more examples, see Granovetter (1978) [Threshold Models of Collective Behavior](#)



[https://www.ted.com/talks/derek\\_sivers\\_how\\_to\\_start\\_a\\_movement#t-169235](https://www.ted.com/talks/derek_sivers_how_to_start_a_movement#t-169235)

Now what happens when people following a threshold rule are placed into a network?  
What kinds of cascades can occur?

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What kinds of cascades can occur?

# A simple model of global cascades on random networks

Duncan J. Watts\*

Department of Sociology, Columbia University New York, NY 10027

Communicated by Murray Gell-Mann, Santa Fe Institute, Santa Fe, NM, February 14, 2002 (received for review May 29, 2001)

Simple model of individual behavior + simple network → complex collective behavior

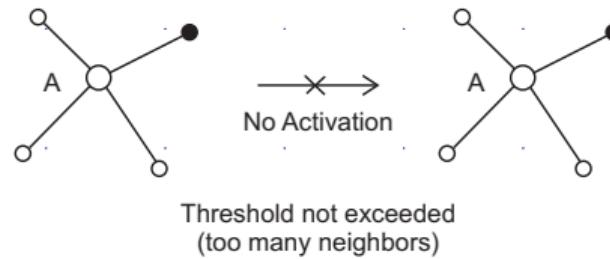
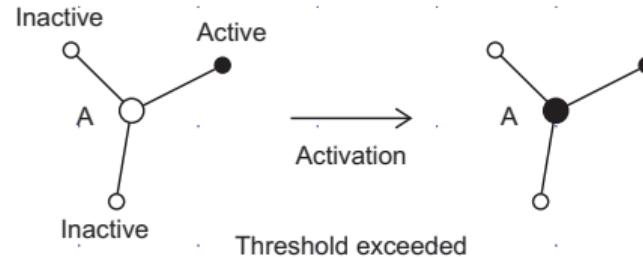
Setup:

- ▶ Homogenous thresholds on Erdos-Reyni random graph
- ▶ All nodes turned off
- ▶ One node randomly turned on

## Setup:

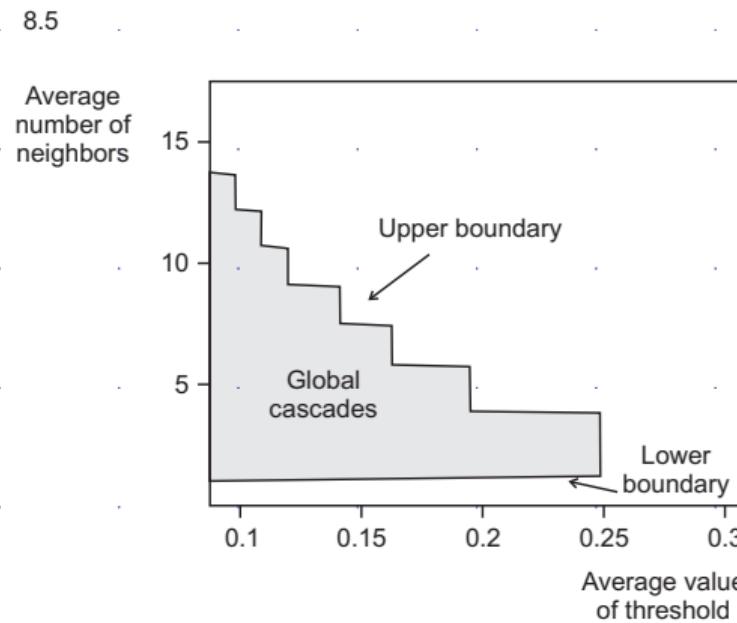
- ▶ Homogenous thresholds on Erdos-Reyni random graph
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8.4



## Setup:

- ▶ Homogenous thresholds on Erdos-Reyni random graph
- ▶ All nodes turned off
- ▶ One node randomly turned on



Note that the percolating vulnerable cluster is not about influential people; it is about easily influenced people



I need your help.  
How can I prevent the riots?

<http://www.princeton.edu/president/eisgruber/who/eisgruber/Indoor.jpg>

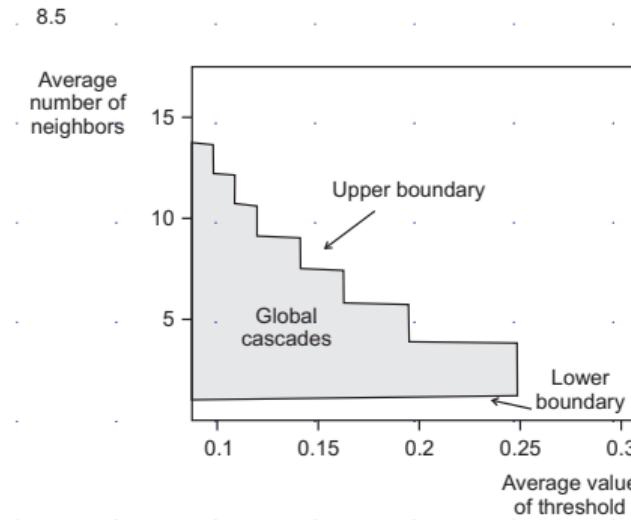
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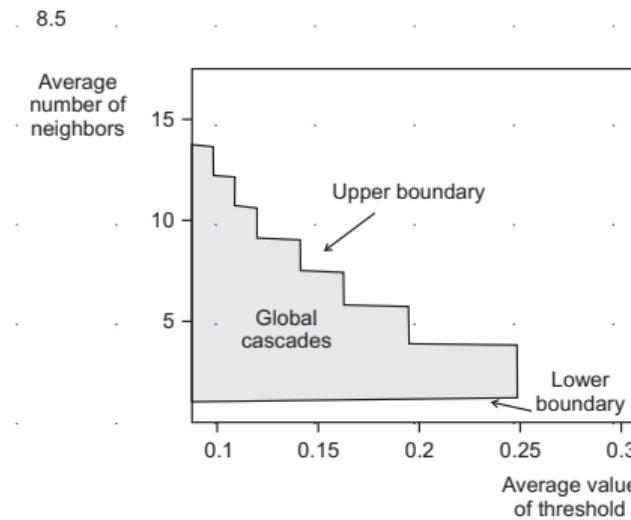
What do you recommend?



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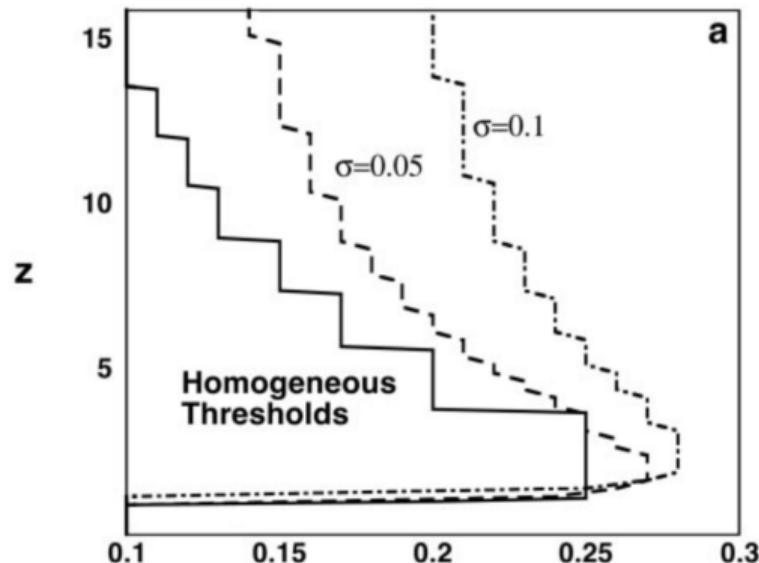
What do you recommend?



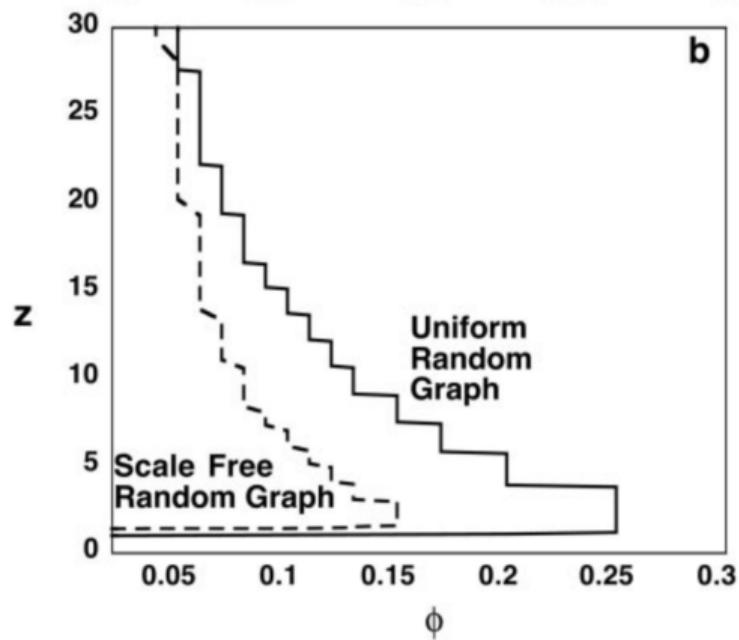
Many approaches. Change connectivity or change thresholds. If you change connectivity, you can decrease the chance of riots by either decreasing or increasing connectivity.

Assumes: Homogenous thresholds on Erdos-Reyni random graph (Watts 2002 calls it “uniform random graph”). What about heterogeneity?

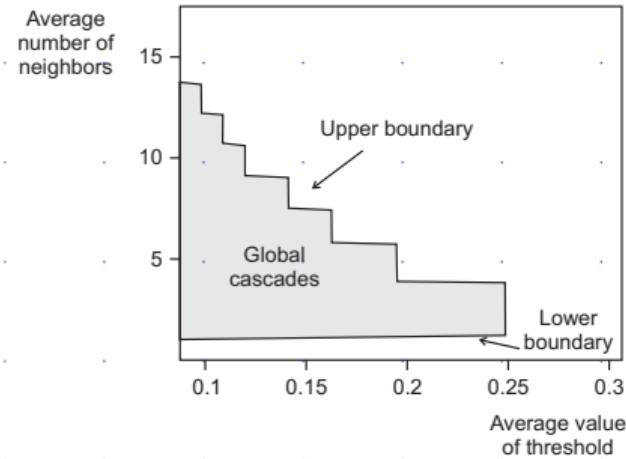
Heterogeneity in thresholds makes cascade window bigger.



Heterogeneity in degree distribution makes cascade window smaller.

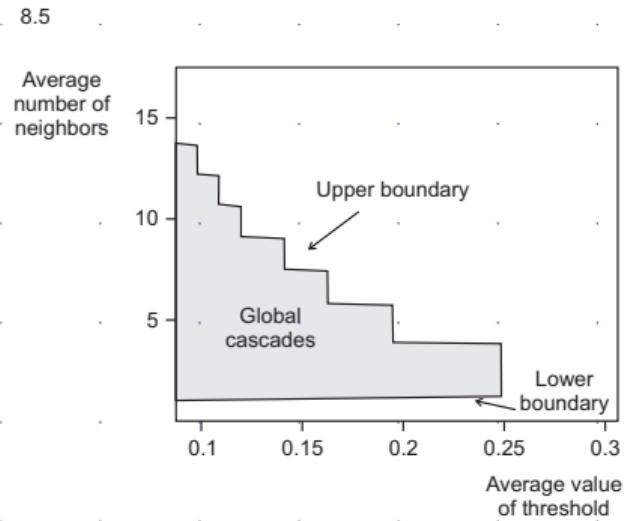


8.5



Think back to the comparison of biological and social contagion.

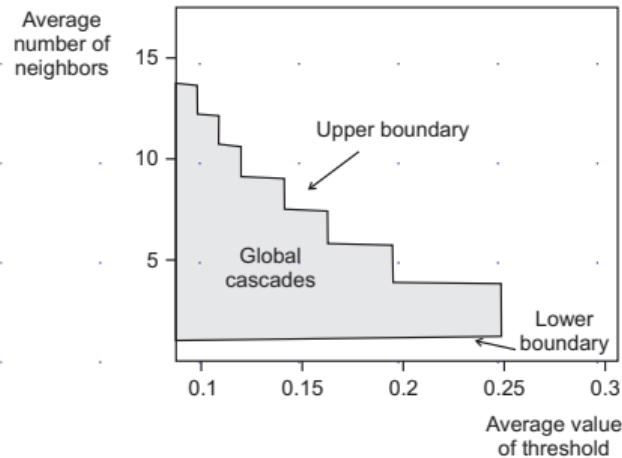
- ▶ In biological contagion what is the effect of increased connectivity?



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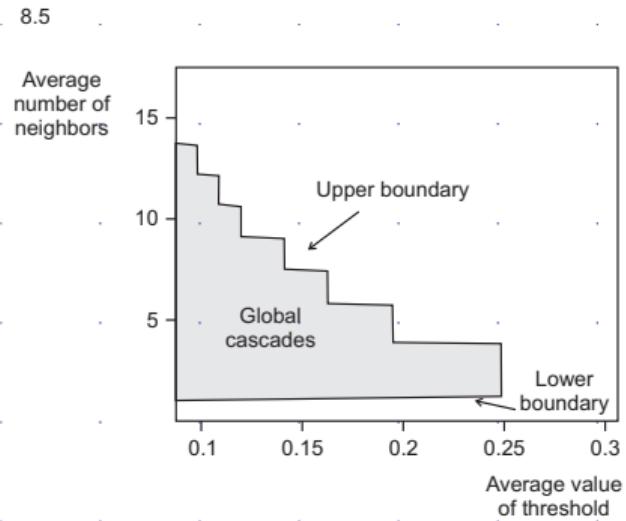
- ▶ In biological contagion what is the effect of increased connectivity? **More spread**

8.5



Think back to the comparison of biological and social contagion.

- ▶ In biological contagion what is the effect of increased connectivity? **More spread**
- ▶ In social contagion what is the effect of increased connectivity?



Think back to the comparison of biological and social contagion.

- ▶ In biological contagion what is the effect of increased connectivity? **More spread**
- ▶ In social contagion what is the effect of increased connectivity? **It depends**

Model in Watts (2002) helps us understand why

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- ▶ global cascades can be triggered by very small shocks
- ▶ global cascades occur rarely despite many shocks that are a priori indistinguishable



**Mohamed Bouazizi**

[http://en.wikipedia.org/wiki/File:Mohamed\\_Bouazizi.jpg](http://en.wikipedia.org/wiki/File:Mohamed_Bouazizi.jpg)



[http://commons.wikimedia.org/wiki/File:Caravane\\_de\\_la\\_lib%C3%A9ration\\_4.jpg](http://commons.wikimedia.org/wiki/File:Caravane_de_la_lib%C3%A9ration_4.jpg)



[http://commons.wikimedia.org/wiki/File:Info\\_box\\_collage\\_for\\_mena\\_Arabic\\_protests.png](http://commons.wikimedia.org/wiki/File:Info_box_collage_for_mena_Arabic_protests.png)

"Packed with evidence on how social media has changed social movements." — *Financial Times*

ZEYNEP  
TUFEKCI

TWITTER  
AND  
TEAR GAS

THE POWER  
AND FRAGILITY  
OF NETWORKED  
PROTEST

One of the Washington Post's 50  
notable works of nonfiction in 2017

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## Summary:

- ▶ disease contagion and social contagion have different micro rules and macro dynamics
- ▶ hard to predict collective outcome from individual preferences and hard to infer individual preferences from collective outcomes
- ▶ sometimes small shocks get big and sometimes they don't

Feedback: <http://bit.ly/soc204-2021>

Next class:

- ▶ Hedstrom, P. (2006). Experimental macro sociology: Predicting the next best seller. *Science*.
- ▶ Salganik, M.J., Dodds, P.S., and Watts, D.J. (2006). Experimental study of inequality and unpredictability in an artificial cultural market. *Science*.
- ▶ Salganik, M.J., and Watts, D.J. (2008). Leading the herd astray: Experimental study of self-fulfilling prophecies in an artificial cultural market. *Social Psychology Quarterly*.