Social Contagion

Principles of Complex Systems
Course 300, Fall, 2008

Prof. Peter Dodds

Department of Mathematics & Statistics
University of Vermont

Outline

Social Contagion Models
Background
Granovetter's model
Network version
Groups
Chaos
References

Outline

Social Contagion

Social Contagion

Social Contagion

Examples abound

- fashion
- striking
- smoking (⊞) [6]
- residential segregation [15]
- ipods
- obesity (⊞) [5]
- Harry Potter
- voting
- gossip
- Rubik's cube 
- religious beliefs
- leaving lectures

SIR and SIRS contagion possible

- Classes of behavior versus specific behavior

Social Contagion

Examples abound

- fashion
- striking
- smoking (⊞) [6]
- residential segregation [15]
- ipods
- obesity (⊞) [5]
- Harry Potter
- voting
- gossip
- Rubik's cube 
- religious beliefs
- leaving lectures

SIR and SIRS contagion possible

- Classes of behavior versus specific behavior

Social Contagion

Examples abound

- fashion
- striking
- smoking (⊞) [6]
- residential segregation [15]
- ipods
- obesity (⊞) [5]
- Harry Potter
- voting
- gossip
- Rubik's cube 
- religious beliefs
- leaving lectures

SIR and SIRS contagion possible

- Classes of behavior versus specific behavior

Social Contagion

Examples abound

- fashion
- striking
- smoking (⊞) [6]
- residential segregation [15]
- ipods
- obesity (⊞) [5]
- Harry Potter
- voting
- gossip
- Rubik's cube 
- religious beliefs
- leaving lectures

SIR and SIRS contagion possible

- Classes of behavior versus specific behavior: dieting

Framingham heart study:

Evolving network stories:

- The spread of quitting smoking (⊞) [6]
- The spread of spreading (⊞) [5]

Social Contagion

Two focuses for us

- Widespread media influence
- Word-of-mouth influence

Social Contagion

Two focuses for us

- Widespread media influence
- Word-of-mouth influence

Social Contagion

Two focuses for us

- Widespread media influence
- Word-of-mouth influence

Social Contagion

We need to understand influence

- Who influences whom?
- What kinds of influence response functions are there?
- Are some individuals super influencers?

- The infectious idea of opinion leaders (Katz and Lazarsfeld) [12]

Social Contagion

We need to understand influence

- Who influences whom?
- What kinds of influence response functions are there?
- Are some individuals super influencers?

- The infectious idea of opinion leaders (Katz and Lazarsfeld) [12]

Social Contagion

We need to understand influence

- Who influences whom? Very hard to measure...
- What kinds of influence response functions are there?
- Are some individuals super influencers?
- The infectious idea of opinion leaders (Katz and Lazarsfeld) [12]

Social Contagion

We need to understand influence

- Who influences whom? Very hard to measure...
- What kinds of influence response functions are there?
- Are some individuals super influencers?
- The infectious idea of opinion leaders (Katz and Lazarsfeld) [12]

Social Contagion

We need to understand influence

- Who influences whom? Very hard to measure...
- What kinds of influence response functions are there?
- Are some individuals super influencers?

- The infectious idea of opinion leaders (Katz and Lazarsfeld) [12]

Social Contagion

We need to understand influence

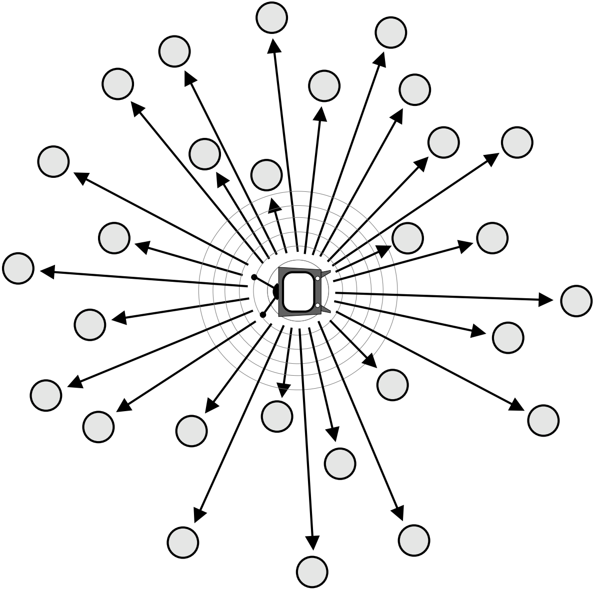
- Who influences whom? Very hard to measure...
- What kinds of influence response functions are there?
- Are some individuals super influencers?
  Highly popularized by Gladwell [8] as 'connectors'
- The infectious idea of opinion leaders (Katz and Lazarsfeld) [12]

Social Contagion

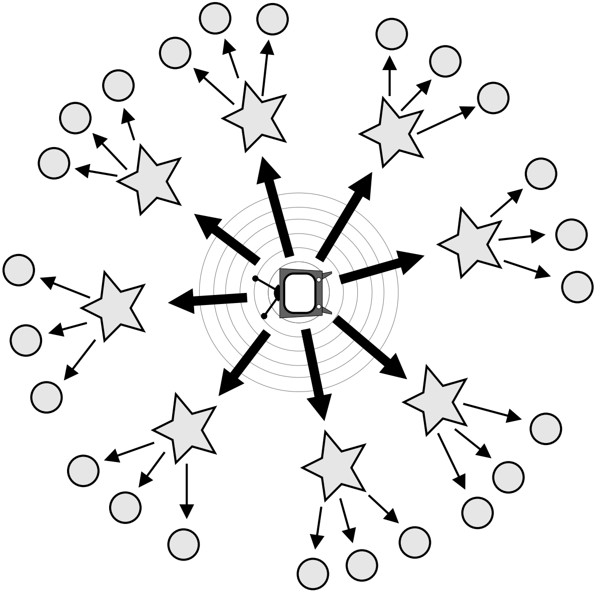
We need to understand influence

- Who influences whom? Very hard to measure...
- What kinds of influence response functions are there?
- Are some individuals super influencers? Highly popularized by Gladwell [8] as ‘connectors’
- The infectious idea of opinion leaders (Katz and Lazarsfeld) [12]

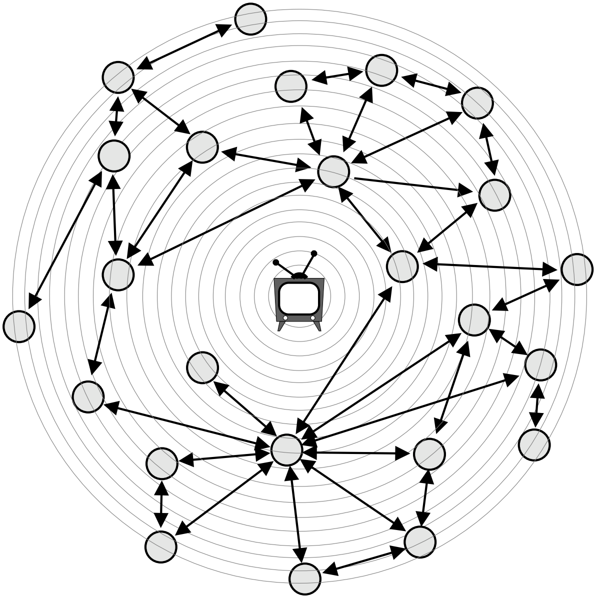
The hypodermic model of influence



The two step model of influence [12]



The general model of influence



Social Contagion

Why do things spread?

- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

Social Contagion

Why do things spread?

- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

Social Contagion

Why do things spread?

- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

Social Contagion

Why do things spread?

- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

Social Contagion

Why do things spread?

- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

Social Contagion

Why do things spread?

- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

Social Contagion

Why do things spread?

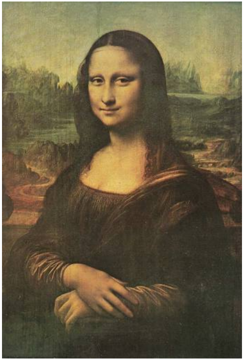
- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

Social Contagion

Why do things spread?

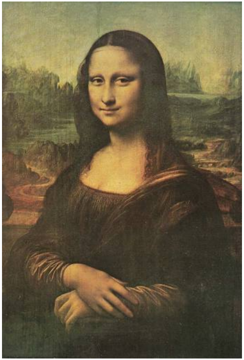
- Because of system level properties?
- Or properties of special individuals?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

The Mona Lisa



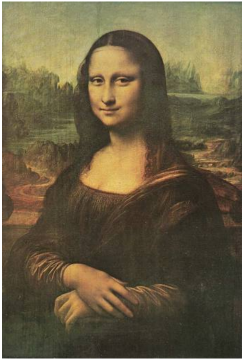
- “Becoming Mona Lisa: The Making of a Global Icon”—David Sassoon
- Not the world’s greatest painting from the start...
- Escalation through theft, vandalism,

The Mona Lisa



- "Becoming Mona Lisa: The Making of a Global Icon"—David Sassoon
- Not the world's greatest painting from the start...
- Escalation through theft, vandalism,

The Mona Lisa



- “Becoming Mona Lisa: The Making of a Global Icon”—David Sassoon
- Not the world’s greatest painting from the start...
- Escalation through theft, vandalism,

The Mona Lisa

- "Becoming Mona Lisa: The Making of a Global Icon"—David Sassoon
- Not the world's greatest painting from the start...
- Escalation through theft, vandalism, parody, ...

The Mona Lisa

- “Becoming Mona Lisa: The Making of a Global Icon”—David Sassoon
- Not the world’s greatest painting from the start...
- Escalation through theft, vandalism, parody, ...

The Mona Lisa

- “Becoming Mona Lisa: The Making of a Global Icon”—David Sassoon
- Not the world’s greatest painting from the start...
- Escalation through theft, vandalism, parody, ...

The completely unpredicted fall of Eastern Europe

Timur Kuran: [13, 14] “Now Out of Never: The Element of Surprise in the East European Revolution of 1989”

The dismal predictive powers of editors...

Social Contagion

Messing with social connections

- Ads based on message content
- Buzz media
- Facebook's advertising: Beacon (⊞)

Social Contagion

Messing with social connections

- Ads based on message content
- Buzz media
- Facebook's advertising: Beacon (⊞)

Social Contagion

Messing with social connections

- Ads based on message content (e.g., Google and email)
- Buzz media
- Facebook's advertising: Beacon (⊞)

Social Contagion

Messing with social connections

- Ads based on message content (e.g., Google and email)
- Buzz media
- Facebook's advertising: Beacon (⊞)

Social Contagion

Messing with social connections

- Ads based on message content (e.g., Google and email)
- Buzz media
- Facebook's advertising: Beacon (⊞)

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Getting others to do things for you

A very good book: 'Influence' by Robert Cialdini [7]

Six modes of influence

1. Reciprocation: *The Old Give and Take... and Take*
2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
6. Scarcity: *The Rule of the Few*

Examples

- Reciprocation: Free samples, Hare Krishnas
- Commitment and Consistency: Hazing
- Social Proof: Catherine Genovese, Jonestown
- Liking: Separation into groups is enough to cause problems.
- Authority: Milgram's obedience to authority experiment.
- Scarcity: Prohibition.

Examples

- Reciprocation: Free samples, Hare Krishnas
- Commitment and Consistency: Hazing
- Social Proof: Catherine Genovese, Jonestown
- Liking: Separation into groups is enough to cause problems.
- Authority: Milgram's obedience to authority experiment.
- Scarcity: Prohibition.

Examples

- Reciprocation: Free samples, Hare Krishnas
- Commitment and Consistency: Hazing
- Social Proof: Catherine Genovese, Jonestown
- Liking: Separation into groups is enough to cause problems.
- Authority: Milgram's obedience to authority experiment.
- Scarcity: Prohibition.

Examples

- Reciprocation: Free samples, Hare Krishnas
- Commitment and Consistency: Hazing
- Social Proof: Catherine Genovese, Jonestown
- Liking: Separation into groups is enough to cause problems.
- Authority: Milgram's obedience to authority experiment.
- Scarcity: Prohibition.

Examples

- Reciprocation: Free samples, Hare Krishnas
- Commitment and Consistency: Hazing
- Social Proof: Catherine Genovese, Jonestown
- Liking: Separation into groups is enough to cause problems.
- Authority: Milgram's obedience to authority experiment.
- Scarcity: Prohibition.

Examples

- Reciprocation: Free samples, Hare Krishnas
- Commitment and Consistency: Hazing
- Social Proof: Catherine Genovese, Jonestown
- Liking: Separation into groups is enough to cause problems.
- Authority: Milgram's obedience to authority experiment.
- Scarcity: Prohibition.

Getting others to do things for you

- Cialdini's modes are heuristics that help up us get through life.
- Useful but can be leveraged...

Getting others to do things for you

- Cialdini's modes are heuristics that help up us get through life.
- Useful but can be leveraged...

Social Contagion

Other acts of influence

- Conspicuous Consumption (Veblen, 1912)
- Conspicuous Destruction (Potlatch)

Social Contagion

Other acts of influence

- Conspicuous Consumption (Veblen, 1912)
- Conspicuous Destruction (Potlatch)

Social Contagion

Other acts of influence

- Conspicuous Consumption (Veblen, 1912)
- Conspicuous Destruction (Potlatch)

Social Contagion

Some important models

- Tipping models—Schelling (1971) [15, 16, 17]
  - Simulation on checker boards
  - Idea of thresholds
  - Fun with Netlogo and Schelling's model [20]...
- Threshold models—Granovetter (1978) [9]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]

Social Contagion

Some important models

- Tipping models—Schelling (1971) [15, 16, 17]
  - Simulation on checker boards
  - Idea of thresholds
  - Fun with Netlogo and Schelling's model [20]...
- Threshold models—Granovetter (1978) [9]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]

Social Contagion

Some important models

- Tipping models—Schelling (1971) [15, 16, 17]
  - Simulation on checker boards
  - Idea of thresholds
  - Fun with Netlogo and Schelling's model [20]...
- Threshold models—Granovetter (1978) [9]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]

Social Contagion

Some important models

- Tipping models—Schelling (1971) [15, 16, 17]
  - Simulation on checker boards
  - Idea of thresholds
  - Fun with Netlogo and Schelling's model [20]...
- Threshold models—Granovetter (1978) [9]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]

Social Contagion

Some important models

- Tipping models—Schelling (1971) [15, 16, 17]
  - Simulation on checker boards
  - Idea of thresholds
  - Fun with Netlogo and Schelling's model [20]...
- Threshold models—Granovetter (1978) [9]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]

Social Contagion

Some important models

- Tipping models—Schelling (1971) [15, 16, 17]
  - Simulation on checker boards
  - Idea of thresholds
  - Fun with Netlogo and Schelling's model [20]...
- Threshold models—Granovetter (1978) [9]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]

Social Contagion

Some important models

- Tipping models—Schelling (1971) [15, 16, 17]
  - Simulation on checker boards
  - Idea of thresholds
  - Fun with Netlogo and Schelling's model [20]...
- Threshold models—Granovetter (1978) [9]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]
  - Social learning theory, Informational cascades,...

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter...
- Assumption: level of influence per person is uniform

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter...
- Assumption: level of influence per person is uniform

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- ‘Others’ may be everyone in a population, an individual’s close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others’ adoption does not matter...
- Assumption: level of influence per person is uniform

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter...
- Assumption: level of influence per person is uniform

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter...
- Assumption: level of influence per person is uniform

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter...
- Assumption: level of influence per person is uniform

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- ‘Others’ may be everyone in a population, an individual’s close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others’ adoption does not matter...
- Assumption: level of influence per person is uniform

Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter... (unrealistic).
- Assumption: level of influence per person is uniform (unrealistic).

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

Outline

Social Contagion Models
- Background
- Granovetter's model
- Network version
- Groups
- Chaos

References

Granovetter's Threshold model—definitions

- ϕ^* = threshold of an individual.
- $f(\phi_*)$ = distribution of thresholds in a population.
- $F(\phi_*)$ = cumulative distribution = $\int_{\phi'_*=0}^{\phi_*} f(\phi'_*)\mathrm{d}\phi'_*$
- ϕ_t = fraction of people 'rioting' at time step t.

Granovetter's Threshold model—definitions

- ϕ^* = threshold of an individual.
- $f(\phi_*)$ = distribution of thresholds in a population.
- $F(\phi_*)$ = cumulative distribution = $\int_{\phi'_*=0}^{\phi_*} f(\phi'_*)\mathrm{d}\phi'_*$
- ϕ_t = fraction of people 'rioting' at time step t.

Granovetter's Threshold model—definitions

- ϕ^* = threshold of an individual.
- $f(\phi_*)$ = distribution of thresholds in a population.
- $F(\phi_*)$ = cumulative distribution = $\int_{\phi'_*=0}^{\phi_*} f(\phi'_*)\mathrm{d}\phi'_*$
- ϕ_t = fraction of people 'rioting' at time step t.

Granovetter's Threshold model—definitions

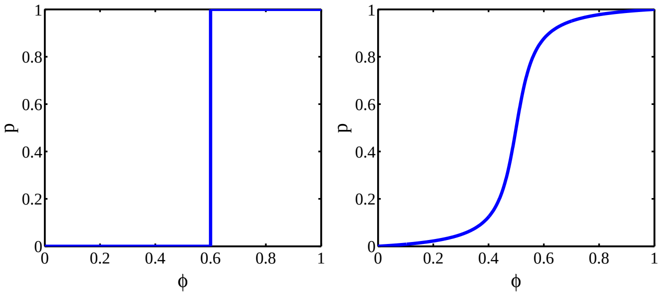
- ϕ^* = threshold of an individual.
- $f(\phi_*)$ = distribution of thresholds in a population.
- $F(\phi_*)$ = cumulative distribution = $\int_{\phi'_*=0}^{\phi_*} f(\phi'_*)\mathrm{d}\phi'_*$
- ϕ_t = fraction of people 'rioting' at time step t.

Social Contagion

Granovetter's Threshold model—definitions

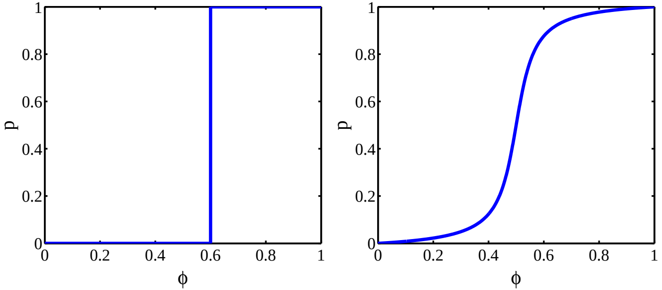
- ϕ^* = threshold of an individual.
- $f(\phi_*)$ = distribution of thresholds in a population.
- $F(\phi_*)$ = cumulative distribution = $\int_{\phi'_*=0}^{\phi_*} f(\phi'_*)\mathrm{d}\phi'_*$
- ϕ_t = fraction of people 'rioting' at time step t.

Threshold models



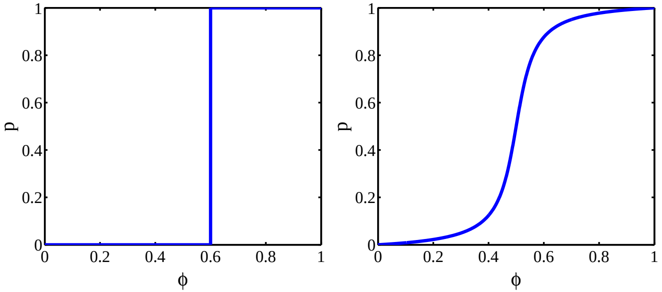
- Example threshold influence response functions: deterministic and stochastic
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Two states: S and I.

Threshold models



- Example threshold influence response functions: deterministic and stochastic
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Two states: S and I.

Threshold models



- Example threshold influence response functions: deterministic and stochastic
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Two states: S and I.

Threshold models

- At time $t + 1$, fraction rioting = fraction with $\phi_* \leq \phi_t$.
-
$$\phi_{t+1} = \int_0^{\phi_t} f(\phi_*) \mathrm{d}\phi_* = F(\phi_*)|_0^{\phi_t} = F(\phi_t)$$
- $\Rightarrow$ Iterative maps of the unit interval $[0, 1]$.

Threshold models

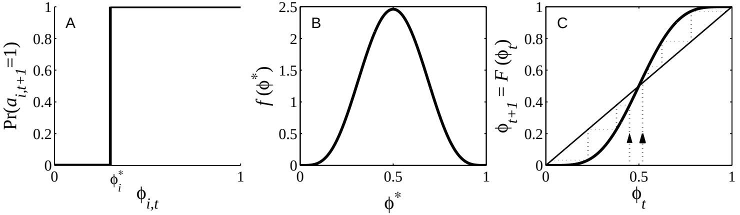
- At time $t + 1$, fraction rioting = fraction with $\phi_* \leq \phi_t$.
- $$\phi_{t+1} = \int_0^{\phi_t} f(\phi_*)\mathrm{d}\phi_* = F(\phi_*)|_0^{\phi_t} = F(\phi_t)$$
- $\Rightarrow$ Iterative maps of the unit interval $[0, 1]$.

Threshold models

- At time $t+1$, fraction rioting = fraction with $\phi_* \leq \phi_t$.
- $$\phi_{t+1} = \int_0^{\phi_t} f(\phi_*)\mathrm{d}\phi_* = F(\phi_*)|_0^{\phi_t} = F(\phi_t)$$
- $\Rightarrow$ Iterative maps of the unit interval $[0, 1]$.

Threshold models

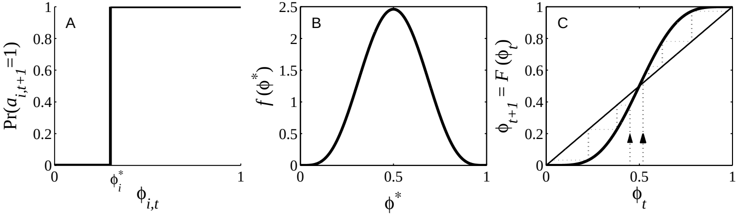
Action based on perceived behavior of others.



- Two states: S and I.
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Discrete time update (strong assumption!)
- This is a Critical mass model

Threshold models

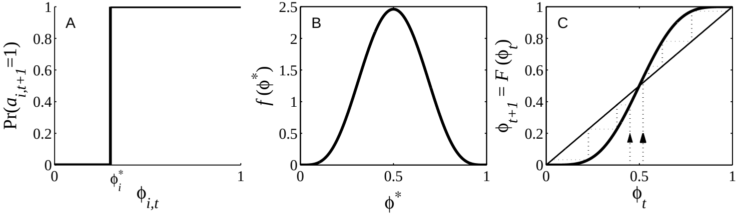
Action based on perceived behavior of others.



- Two states: S and I.
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Discrete time update (strong assumption!)
- This is a Critical mass model

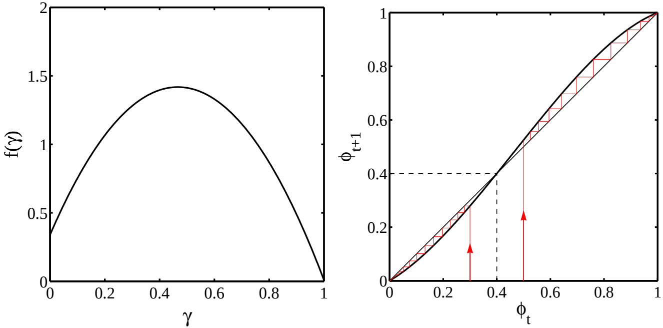
Threshold models

Action based on perceived behavior of others.



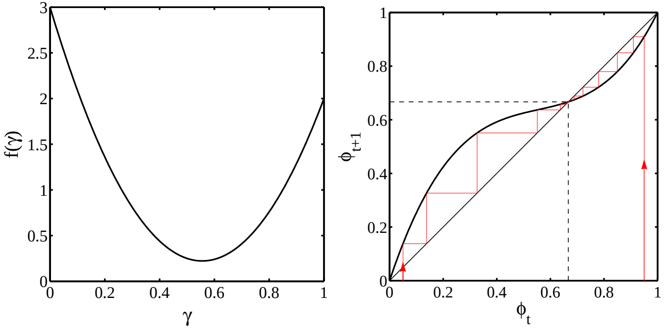
- Two states: S and I.
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Discrete time update (strong assumption!)
- This is a Critical mass model

Threshold models



- Another example of critical mass model...

Threshold models



- Example of single stable state model

Threshold models

Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity
2. Small individual changes $\Rightarrow$ large global changes

Threshold models

Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity
2. Small individual changes $\Rightarrow$ large global changes

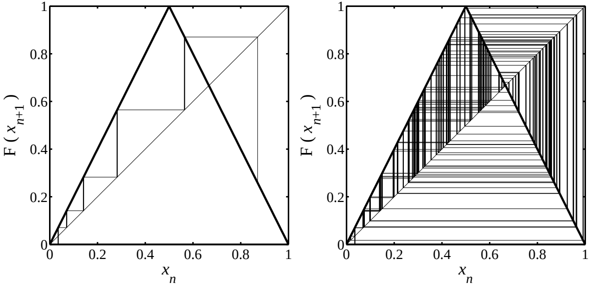
Threshold models

Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity
2. Small individual changes $\Rightarrow$ large global changes

Threshold models

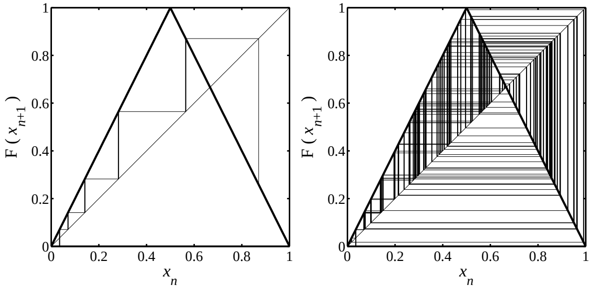
Chaotic behavior possible [11, 10]



- Period doubling arises as map amplitude r is increased.
- Synchronous update assumption is crucial

Threshold models

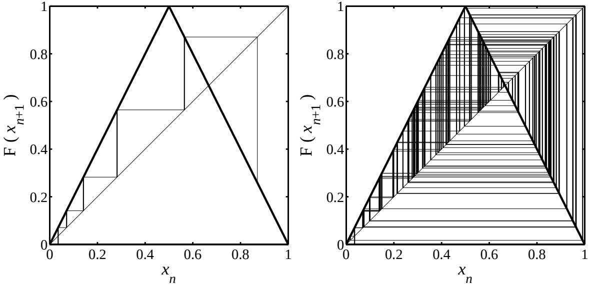
Chaotic behavior possible [11, 10]



- Period doubling arises as map amplitude r is increased.
- Synchronous update assumption is crucial

Threshold models

Chaotic behavior possible [11, 10]



- Period doubling arises as map amplitude r is increased.
- Synchronous update assumption is crucial

Outline

Threshold model on a network

Many years after Granovetter and Soong's work:

"A simple model of global cascades on random networks"
D. J. Watts. Proc. Natl. Acad. Sci., 2002 [19]

- Mean field model → network model
- Individuals now have a limited view of the world

Threshold model on a network

Many years after Granovetter and Soong's work:

"A simple model of global cascades on random networks"
D. J. Watts. Proc. Natl. Acad. Sci., 2002 [19]

- Mean field model $\rightarrow$ network model
- Individuals now have a limited view of the world

Threshold model on a network

Many years after Granovetter and Soong's work:

"A simple model of global cascades on random networks"
D. J. Watts. Proc. Natl. Acad. Sci., 2002 [19]

- Mean field model → network model
- Individuals now have a limited view of the world

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

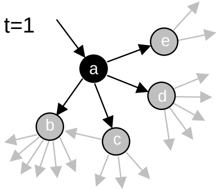
Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network

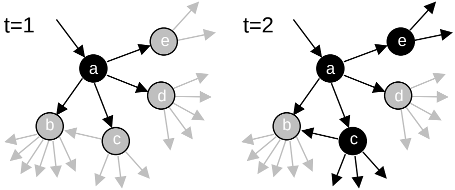
- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $a_i \geq \phi_i k_i$
- Individuals remain active when switched (no recovery = SI model)

Threshold model on a network



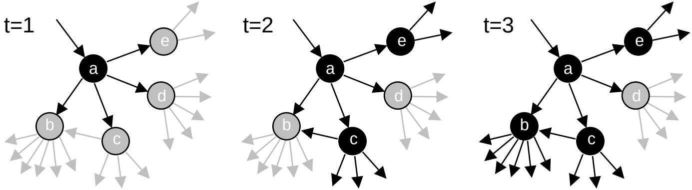
- All nodes have threshold $\phi = 0.2$.

Threshold model on a network



- All nodes have threshold $\phi = 0.2$.

Threshold model on a network



- All nodes have threshold $\phi = 0.2$.

Snowballing

The Cascade Condition:

If one individual is initially activated, what is the probability that an activation will spread over a network?

Snowballing

The Cascade Condition:

If one individual is initially activated, what is the probability that an activation will spread over a network?

What features of a network determine whether a cascade will occur or not?

Snowballing

First study random networks:

- Start with N nodes with a degree distribution p_k
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition

Snowballing

First study random networks:

- Start with N nodes with a degree distribution p_k
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition

Snowballing

First study random networks:

- Start with N nodes with a degree distribution p_k
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition

Snowballing

First study random networks:

- Start with N nodes with a degree distribution p_k
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition

Snowballing

First study random networks:

- Start with N nodes with a degree distribution p_k
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition

Snowballing

Follow active links

- An active link is a link connected to an activated node.
- If an infected link leads to at least 1 more infected link, then activation spreads.
- We need to understand which nodes can be activated when only one of their neigbors becomes active.

Snowballing

Follow active links

- An active link is a link connected to an activated node.
- If an infected link leads to at least 1 more infected link, then activation spreads.
- We need to understand which nodes can be activated when only one of their neigbors becomes active.

Snowballing

Follow active links

- An active link is a link connected to an activated node.
- If an infected link leads to at least 1 more infected link, then activation spreads.
- We need to understand which nodes can be activated when only one of their neigbors becomes active.

Snowballing

Follow active links

- An active link is a link connected to an activated node.
- If an infected link leads to at least 1 more infected link, then activation spreads.
- We need to understand which nodes can be activated when only one of their neigbors becomes active.

The most gullible

Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [19]
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

The most gullible

Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables*[19]
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

The most gullible

Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [19]
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

The most gullible

Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [19]
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

The most gullible

Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables*[19]
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

The most gullible

Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [19]
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

The most gullible

Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [19]
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

Cascade condition

Back to following a link:

- Link from leads to a node with probability $\propto kP_k$.
- Follows from links being random + having k chances to connect to a node with degree k.
- Normalization:

$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle = z$$

- So

$$P(\text{linked node has degree } k) = \frac{kP_k}{\langle k \rangle}$$

Cascade condition

Back to following a link:

- Link from leads to a node with probability $\propto kP_k$.
- Follows from links being random + having k chances to connect to a node with degree k.
- Normalization:

$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle = z$$

- So

$$P(\text{linked node has degree } k) = \frac{kP_k}{\langle k \rangle}$$

Cascade condition

Back to following a link:

- Link from leads to a node with probability $\propto kP_k$.
- Follows from links being random + having k chances to connect to a node with degree k.
- Normalization:

$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle = z$$

- So

$$P(\text{linked node has degree } k) = \frac{kP_k}{\langle k \rangle}$$

Cascade condition

Back to following a link:

- Link from leads to a node with probability $\propto kP_k$.
- Follows from links being random + having k chances to connect to a node with degree k.
- Normalization:

$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle = z$$

- So

$$P(\text{linked node has degree } k) = \frac{kP_k}{\langle k \rangle}$$

Cascade condition

Back to following a link:

- Link from leads to a node with probability $\propto kP_k$.
- Follows from links being random + having k chances to connect to a node with degree k.
- Normalization:

$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle = z$$

- So

$$P(\text{linked node has degree } k) = \frac{kP_k}{\langle k \rangle}$$

Cascade condition

Next: Vulnerability of linked node

- Linked node is vulnerable with probability

$$\beta_k = \int_{\phi'_*=0}^{1/k} f(\phi'_*) \mathrm{d}\phi'_*$$

- If linked node is vulnerable, it produces $k - 1$ new outgoing active links
- If linked node is not vulnerable, it produces no active links.

Cascade condition

Next: Vulnerability of linked node

- Linked node is vulnerable with probability

$$\beta_k = \int_{\phi'_*=0}^{1/k} f(\phi'_*)\mathrm{d}\phi'_*$$

- If linked node is vulnerable, it produces $k-1$ new outgoing active links
- If linked node is not vulnerable, it produces no active links.

Cascade condition

Next: Vulnerability of linked node

- Linked node is vulnerable with probability

$$\beta_k = \int_{\phi'_*=0}^{1/k} f(\phi'_*)\mathrm{d}\phi'_*$$

- If linked node is vulnerable, it produces $k-1$ new outgoing active links
- If linked node is not vulnerable, it produces no active links.

Cascade condition

Next: Vulnerability of linked node

- Linked node is vulnerable with probability

$$\beta_k = \int_{\phi'_*=0}^{1/k} f(\phi'_*)\mathrm{d}\phi'_*$$

- If linked node is vulnerable, it produces $k-1$ new outgoing active links
- If linked node is not vulnerable, it produces no active links.

Cascade condition

Putting things together:

- Expected number of active edges produced by an active edge =
- $$\sum_{k=1}^{\infty} \underbrace{(k-1)\beta_k \frac{kP_k}{z}}_{\text{success}} +$$
- $$= \sum_{k=1}^{\infty} (k-1)k\beta_k P_k / z$$

Cascade condition

Putting things together:

- Expected number of active edges produced by an active edge =
- $$\sum_{k=1}^{\infty} \underbrace{(k-1)\beta_k \frac{kP_k}{z}}_{\text{success}} +$$
- $$= \sum_{k=1}^{\infty} (k-1) k \beta_k P_k / z$$

Cascade condition

Putting things together:

- Expected number of active edges produced by an active edge =
- $$\sum_{k=1}^{\infty} \underbrace{(k-1)\beta_k \frac{kP_k}{z}}_{\text{success}} + \underbrace{0(1-\beta_k)\frac{kP_k}{z}}_{\text{failure}}$$
- $$= \sum_{k=1}^{\infty} (k-1)k\beta_k P_k / z$$

Cascade condition

Putting things together:

- Expected number of active edges produced by an active edge =
- $$\sum_{k=1}^{\infty} \underbrace{(k-1)\beta_k \frac{kP_k}{z}}_{\text{success}} + \underbrace{0(1-\beta_k)\frac{kP_k}{z}}_{\text{failure}}$$
- $$= \sum_{k=1}^{\infty} (k-1)k\beta_k P_k / z$$

Cascade condition

So... for random networks with fixed degree distributions, cacades take off when:

$$\sum_{k=1}^{\infty} k(k-1)\beta_k P_k / z \geq 1.$$

- β_k = probability a degree k node is vulnerable.
- P_k = probability a node has degree k.

Cascade condition

Two special cases:

- (1) Simple disease-like spreading succeeds: $\beta_k = \beta$
- $$\beta \sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$
- (2) Giant component exists: $\beta = 1$
- $$\sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$

Cascade condition

Two special cases:

- (1) Simple disease-like spreading succeeds: $\beta_k = \beta$
-
$$\beta \sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$
- (2) Giant component exists: $\beta = 1$
-
$$\sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$

Cascade condition

Two special cases:

- (1) Simple disease-like spreading succeeds: $\beta_k = \beta$
- $$\beta \sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$
- (2) Giant component exists: $\beta = 1$
- $$\sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$

Cascade condition

Two special cases:

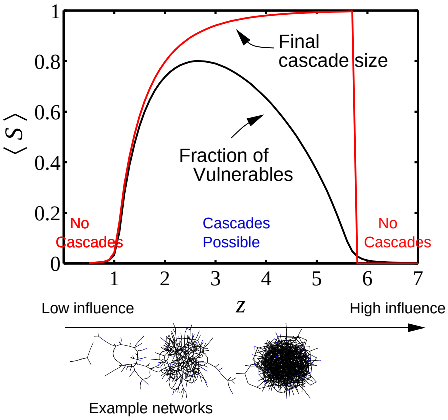
- (1) Simple disease-like spreading succeeds: $\beta_k = \beta$
- $$\beta \sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$
- (2) Giant component exists: $\beta = 1$
- $$\sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$

Cascade condition

Two special cases:

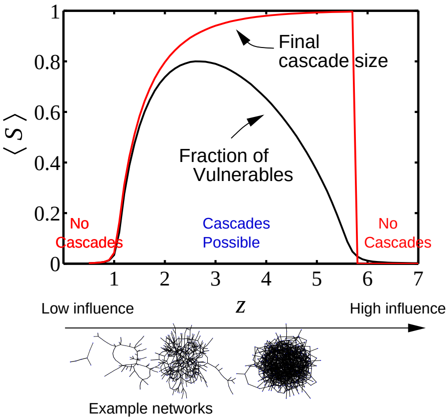
- (1) Simple disease-like spreading succeeds: $\beta_k = \beta$
- $$\beta \sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$
- (2) Giant component exists: $\beta = 1$
- $$\sum_{k=1}^{\infty} k(k-1)P_k/z \geq 1.$$

Cascades on random networks



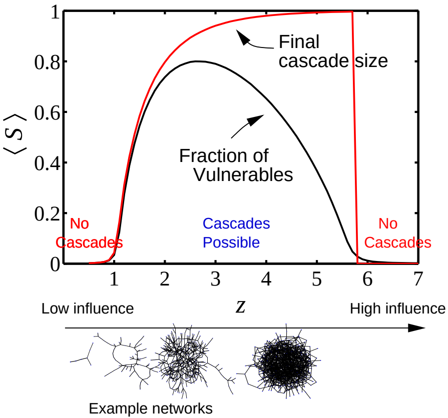
- Cascades occur only if size of max vulnerable cluster > 0.
- System may be 'robust-yet-fragile'.
- 'Ignorance' facilitates spreading.

Cascades on random networks



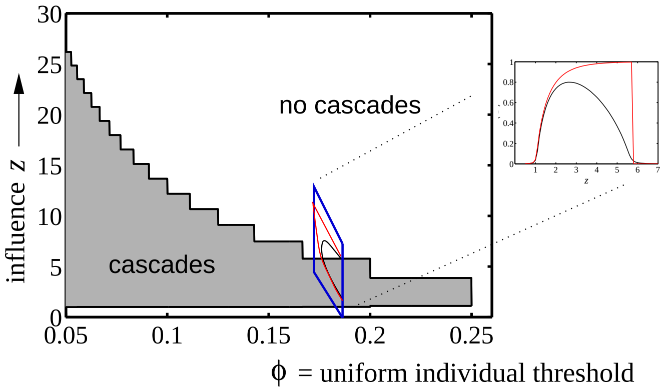
- Cascades occur only if size of max vulnerable cluster > 0.
- System may be 'robust-yet-fragile'.
- 'Ignorance' facilitates spreading.

Cascades on random networks



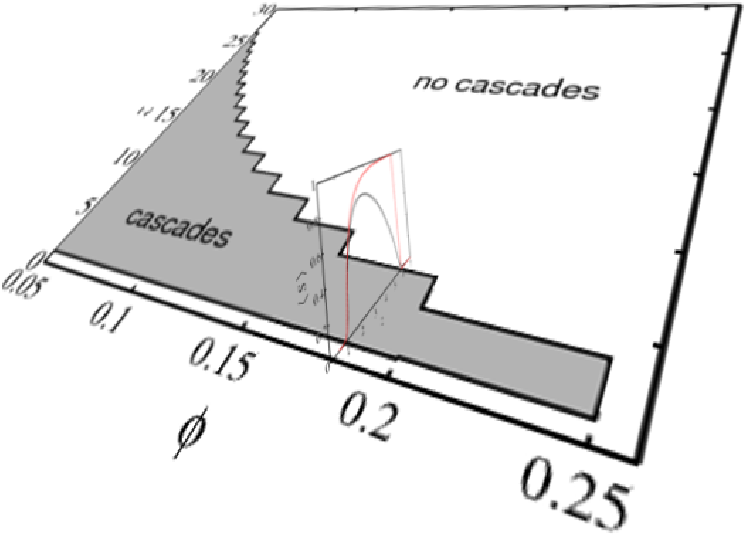
- Cascades occur only if size of max vulnerable cluster > 0.
- System may be 'robust-yet-fragile'.
- 'Ignorance' facilitates spreading.

Cascade window for random networks



- ‘Cascade window’ widens as threshold ϕ decreases.
- Lower thresholds enable spreading.

Cascade window for random networks



Cascade window—summary

For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks. No global clusters of any kind.
2. High $\langle k \rangle$: Giant component exists but not enough vulnerables.
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists. Cascades are possible in "Cascade window."

Cascade window—summary

For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks. No global clusters of any kind.
2. High $\langle k \rangle$: Giant component exists but not enough vulnerables.
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists. Cascades are possible in "Cascade window."

Cascade window—summary

For our simple model of a uniform threshold:

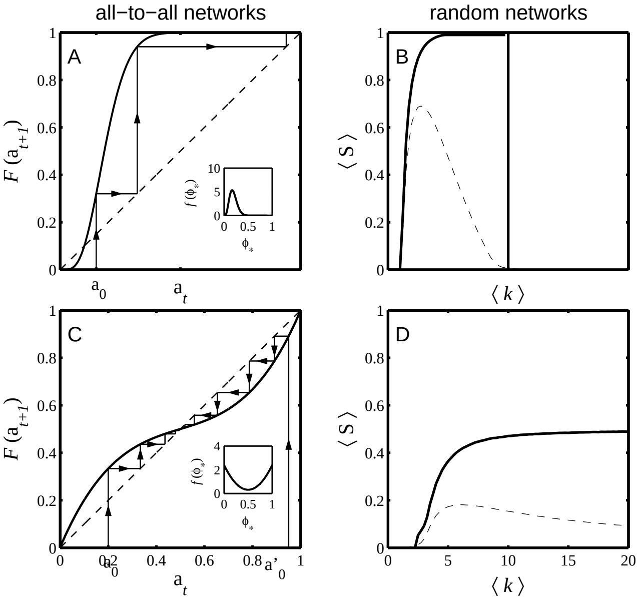
1. Low $\langle k \rangle$: No cascades in poorly connected networks. No global clusters of any kind.
2. High $\langle k \rangle$: Giant component exists but not enough vulnerables.
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists. Cascades are possible in "Cascade window."

Cascade window—summary

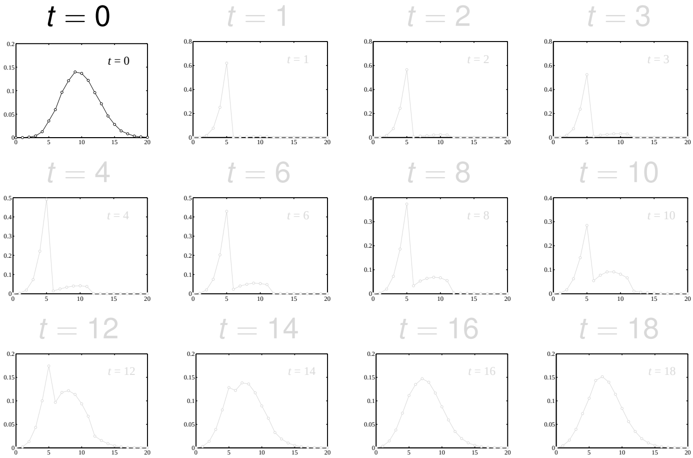
For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks. No global clusters of any kind.
2. High $\langle k \rangle$: Giant component exists but not enough vulnerables.
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists. Cascades are possible in "Cascade window."

All-to-all versus random networks

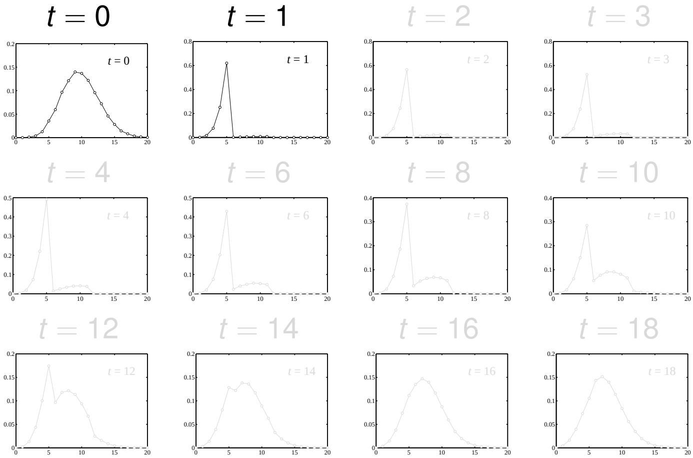


Early adopters—degree distributions



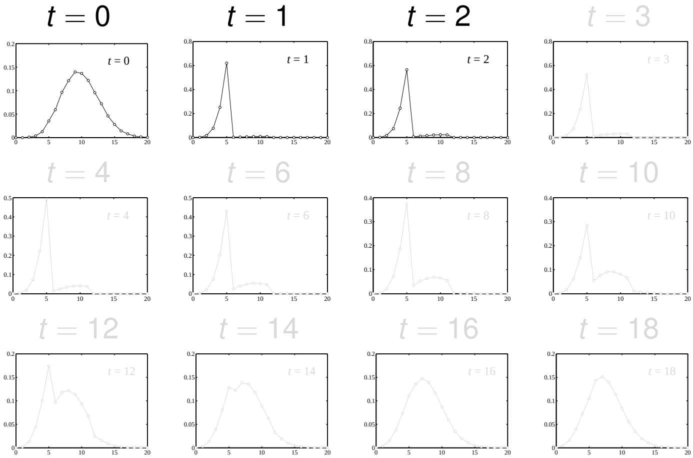
$P_{k,t}$ versus k

Early adopters—degree distributions



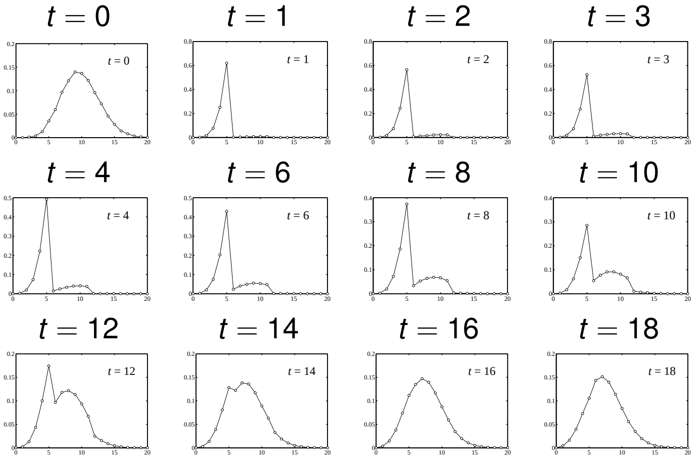
$P_{k,t}$ versus k

Early adopters—degree distributions



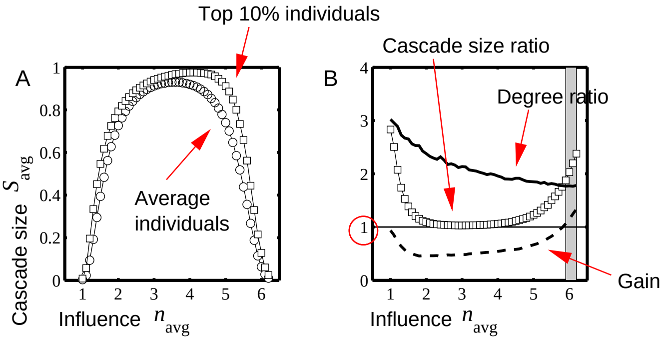
$P_{k,t}$ versus k

Early adopters—degree distributions



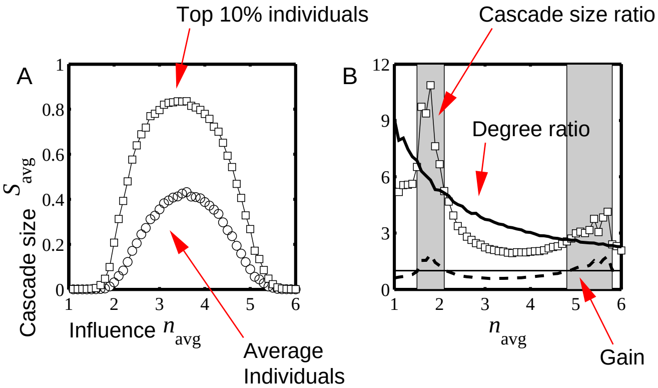
$P_{k,t}$ versus k

The multiplier effect:



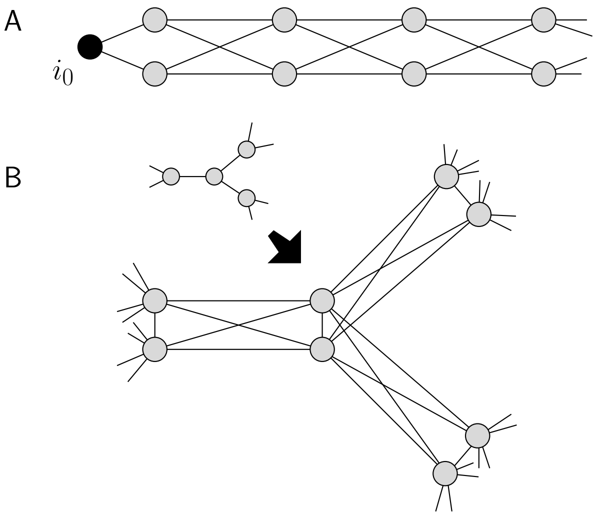
- Fairly uniform levels of individual influence.
- Multiplier effect is mostly below 1.

The multiplier effect:



- Skewed influence distribution example.

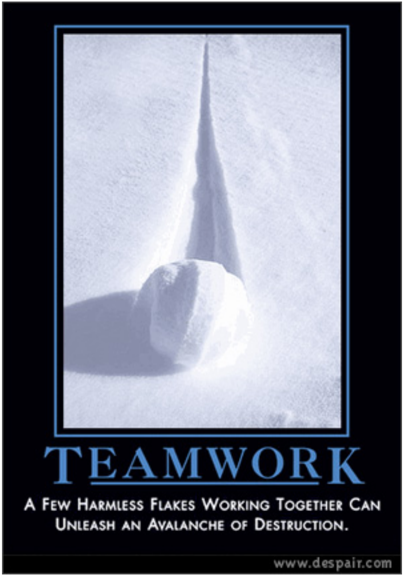
Special subnetworks can act as triggers



- $\phi = 1/3$ for all nodes

Outline

The power of groups...



despair.com

"A few harmless flakes working together can unleash an avalanche of destruction."

Extensions

- Assumption of sparse interactions is good
- Degree distribution is (generally) key to a network's function
- Still, random networks don't represent all networks
- Major element missing: group structure

Extensions

- Assumption of sparse interactions is good
- Degree distribution is (generally) key to a network's function
- Still, random networks don't represent all networks
- Major element missing: group structure

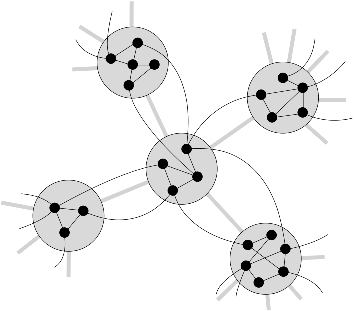
Extensions

- Assumption of sparse interactions is good
- Degree distribution is (generally) key to a network's function
- Still, random networks don't represent all networks
- Major element missing: group structure

Extensions

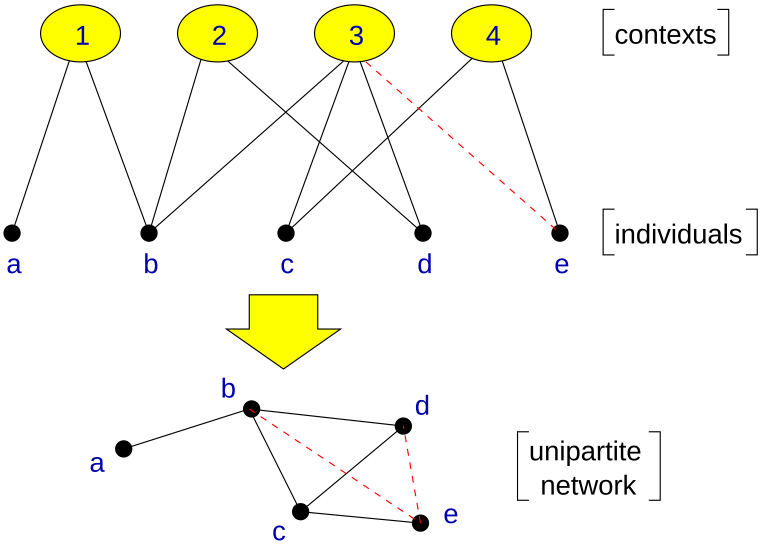
- Assumption of sparse interactions is good
- Degree distribution is (generally) key to a network's function
- Still, random networks don't represent all networks
- Major element missing: group structure

Group structure—Ramified random networks

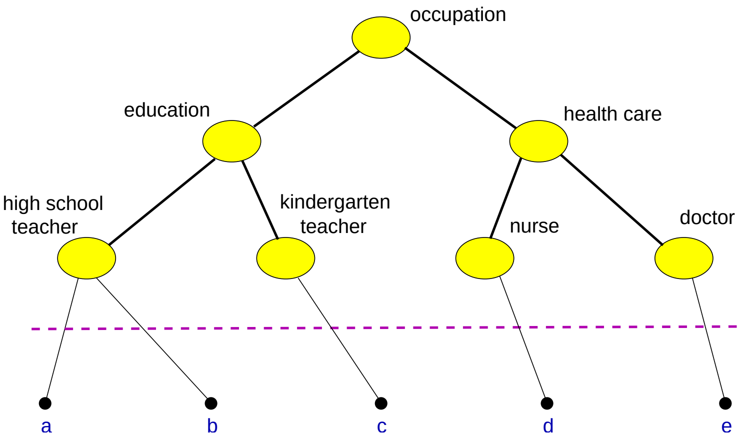


p = intergroup connection probability
q = intragroup connection probability.

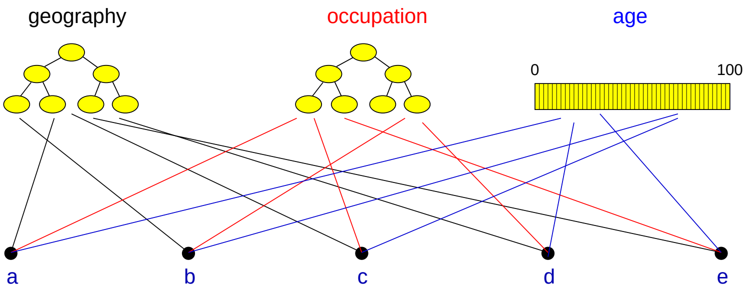
Bipartite networks



Context distance



Generalized affiliation model



(Blau & Schwartz, Simmel, Breiger)

Generalized affiliation model networks with triadic closure

- Connect nodes with probability $\propto \exp^{-\alpha d}$
  where
  α = homophily parameter
  and
  d = distance between nodes (height of lowest common ancestor)
- τ_1 = intergroup probability of friend-of-friend connection
- τ_2 = intragroup probability of friend-of-friend connection

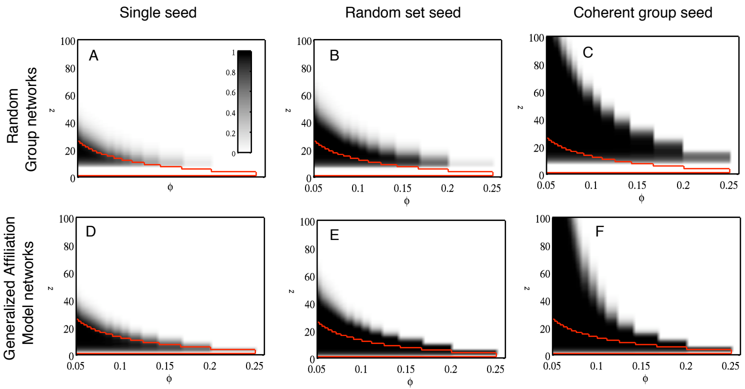
Generalized affiliation model networks with triadic closure

- Connect nodes with probability $\propto \exp^{-\alpha d}$
  where
  α = homophily parameter
  and
  d = distance between nodes (height of lowest common ancestor)
- τ_1 = intergroup probability of friend-of-friend connection
- τ_2 = intragroup probability of friend-of-friend connection

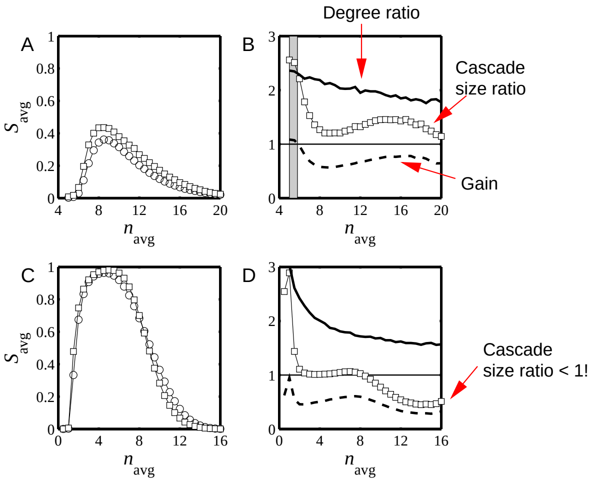
Generalized affiliation model networks with triadic closure

- Connect nodes with probability $\propto \exp^{-\alpha d}$
  where
  α = homophily parameter
  and
  d = distance between nodes (height of lowest common ancestor)
- τ_1 = intergroup probability of friend-of-friend connection
- τ_2 = intragroup probability of friend-of-friend connection

Cascade windows for group-based networks

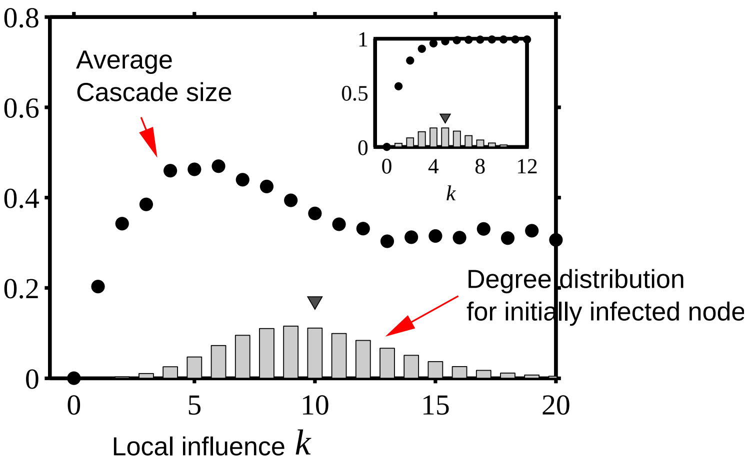


Multiplier effect for group-based networks:



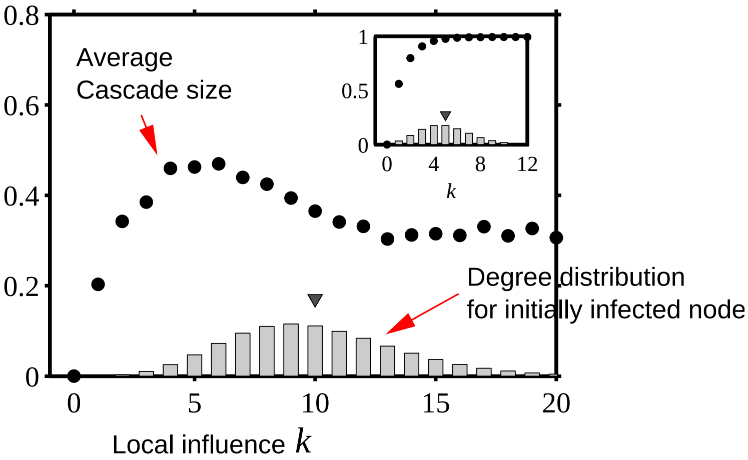
- Multiplier almost always below 1.

Assortativity in group-based networks



- The most connected nodes aren't always the most 'influential.'
- Degree assortativity is the reason.

Assortativity in group-based networks



- The most connected nodes aren't always the most 'influential.'
- Degree assortativity is the reason.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.

Social contagion

Summary

- ‘Influential vulnerables’ are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- ‘Influentials’ are posterior constructs.
- Many potential influentials exist.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.

Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- 'Influentials' are posterior constructs.
- Many potential influentials exist.

Social contagion

Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
- Entities can be novel or designed to combine with others, e.g. block another one.

Social contagion

Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
- Entities can be novel or designed to combine with others, e.g. block another one.

Social contagion

Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
- Entities can be novel or designed to combine with others, e.g. block another one.

Social contagion

Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
- Entities can be novel or designed to combine with others, e.g. block another one.

Social contagion

Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
- Entities can be novel or designed to combine with others, e.g. block another one.

Social contagion

Implications

- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
- Entities can be novel or designed to combine with others, e.g. block another one.

Outline

Chaotic contagion:

- What if individual response functions are not monotonic?
- Consider a simple deterministic version:

- Node i has an 'activation threshold' $\phi_{i,1}$

  ...and a 'de-activation threshold' $\phi_{i,2}$

- Nodes like to imitate but only up to a limit—they don't want to be like everyone else.

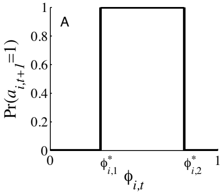
Chaotic contagion:

- What if individual response functions are not monotonic?
- Consider a simple deterministic version:

- Node i has an 'activation threshold' $\phi_{i,1}$

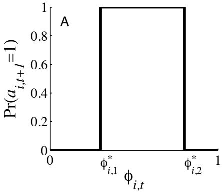
  ...and a 'de-activation threshold' $\phi_{i,2}$

- Nodes like to imitate but only up to a limit—they don't want to be like everyone else.



Chaotic contagion:

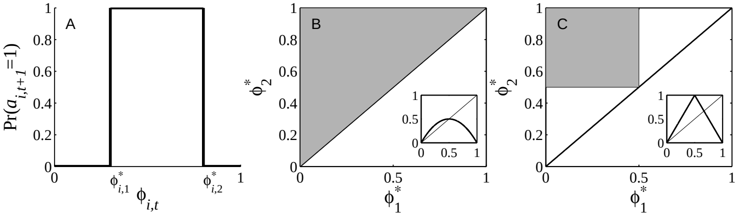
- What if individual response functions are not monotonic?
- Consider a simple deterministic version:



- Node i has an 'activation threshold' $\phi_{i,1}$

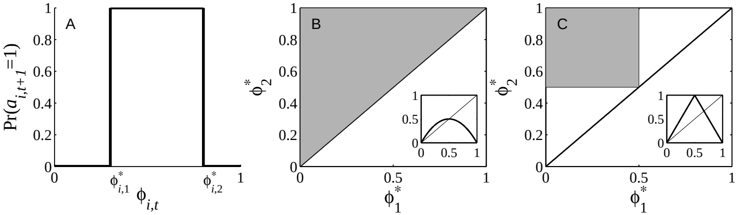
  ... and a 'de-activation threshold' $\phi_{i,2}$
- Nodes like to imitate but only up to a limit—they don't want to be like everyone else.

Two population examples:



- Randomly select $(\phi_{i,1}, \phi_{i,2})$ from gray regions shown in plots B and C.
- Insets show composite response function averaged over population.
- We'll consider plot C's example: the tent map.

Two population examples:



- Randomly select $(\phi_{i,1}, \phi_{i,2})$ from gray regions shown in plots B and C.
- Insets show composite response function averaged over population.
- We'll consider plot C's example: the tent map.

Chaotic contagion

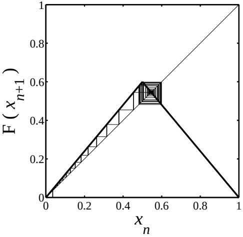
Definition of the tent map:

$$F(x) = \begin{cases} rx \text{ for } 0 \le x \le \frac{1}{2}, \\ r(1-x) \text{ for } \frac{1}{2} \le x \le 1. \end{cases}$$

- The usual business: look at how F iteratively maps the unit interval $[0,1]$.

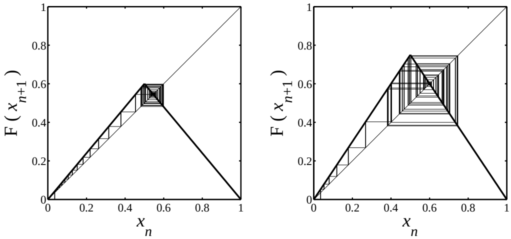
The tent map

Effect of increasing r from 1 to 2.



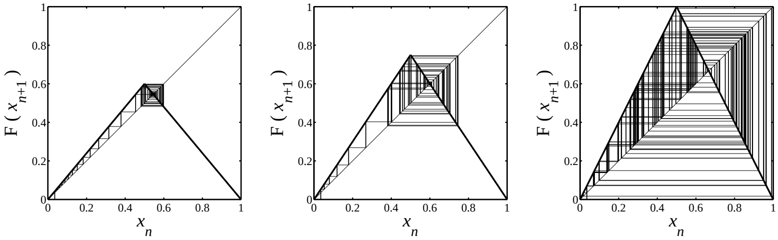
The tent map

Effect of increasing r from 1 to 2.



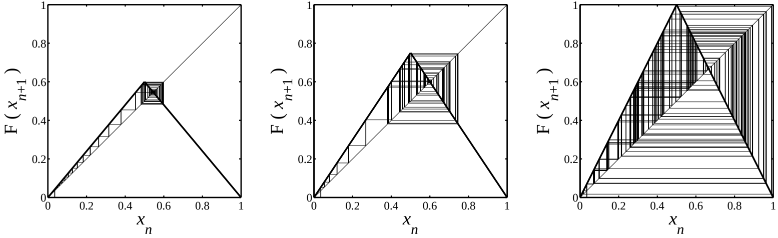
The tent map

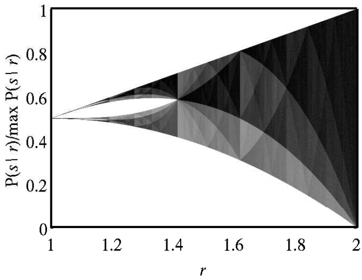
Effect of increasing r from 1 to 2.



The tent map

Effect of increasing r from 1 to 2.



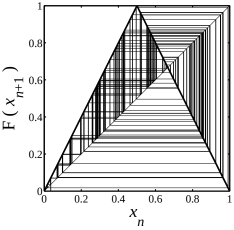


Orbit diagram:

Chaotic behavior increases as map slope r is increased.

Chaotic behavior

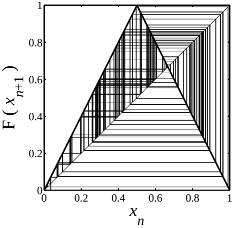
Take $r = 2$ case:



- What happens if nodes have limited information?
- As before, allow interactions to take place on a sparse random network.
- Vary average degree $z = \langle k \rangle$, a measure of information

Chaotic behavior

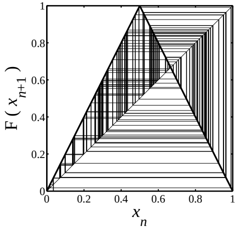
Take $r = 2$ case:



- What happens if nodes have limited information?
- As before, allow interactions to take place on a sparse random network.
- Vary average degree $z = \langle k \rangle$, a measure of information

Chaotic behavior

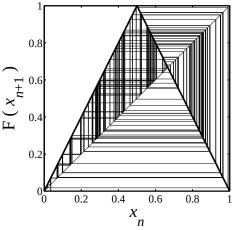
Take $r = 2$ case:



- What happens if nodes have limited information?
- As before, allow interactions to take place on a sparse random network.
- Vary average degree $z = \langle k \rangle$, a measure of information

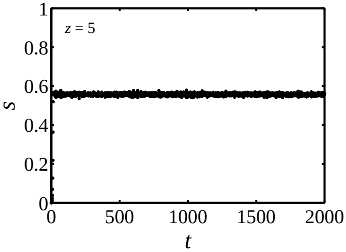
Chaotic behavior

Take $r = 2$ case:

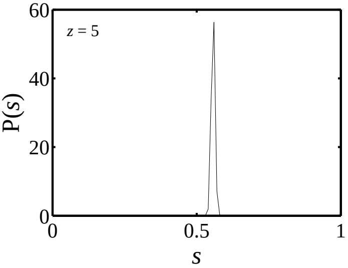


- What happens if nodes have limited information?
- As before, allow interactions to take place on a sparse random network.
- Vary average degree $z = \langle k \rangle$, a measure of information

Invariant densities—stochastic response functions

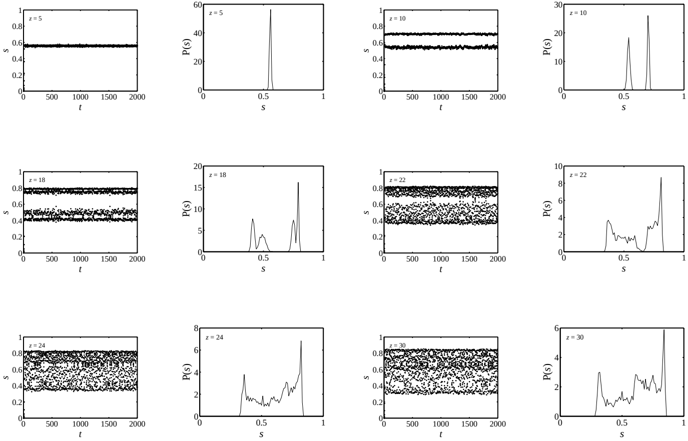


activation time series

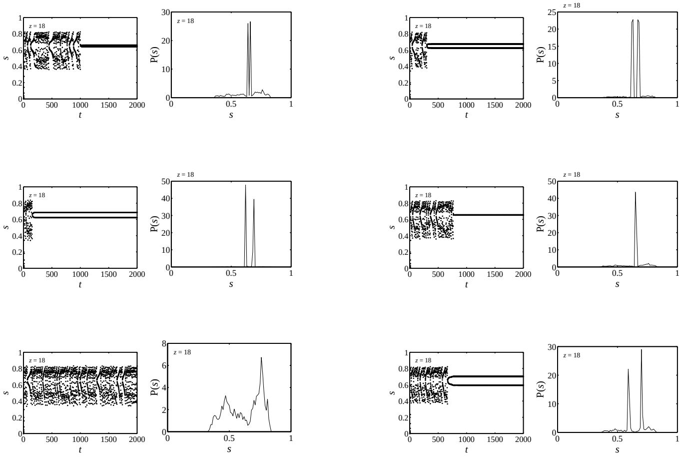


activation density

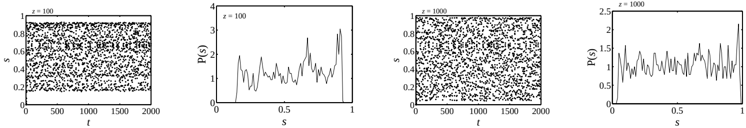
Invariant densities—stochastic response functions



Invariant densities—deterministic response functions for one specific network with $\langle k \rangle = 18$

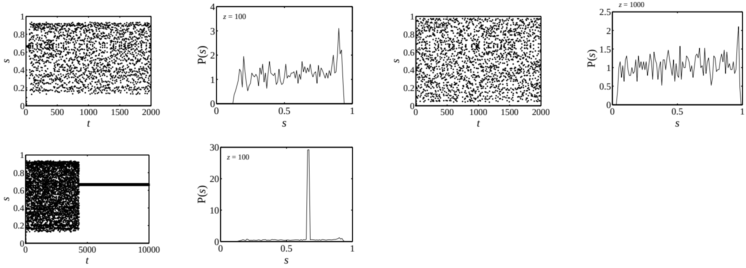


Invariant densities—stochastic response functions



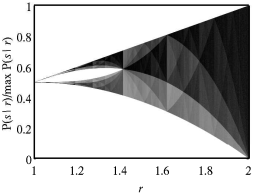
Trying out higher values of $\langle k \rangle$...

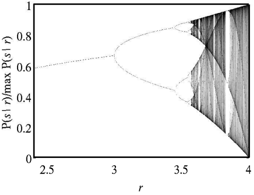
Invariant densities—deterministic response functions



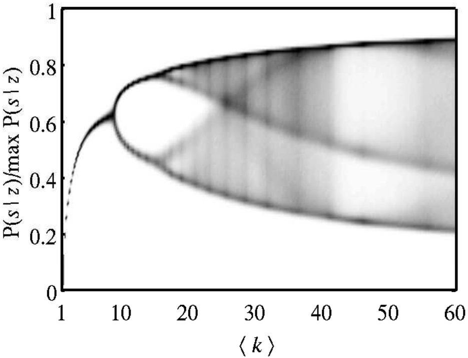
Trying out higher values of $\langle k \rangle$...

Connectivity leads to chaos:





Stochastic response functions:



Chaotic behavior in coupled systems

Coupled maps are well explored (Kaneko/Kuramoto):

$$x_{i,n+1} = f(x_{i,n}) + \sum_{j \in \mathcal{N}_i} \delta_{i,j} f(x_{j,n})$$

- $\mathcal{N}_i$ = neighborhood of node i

1. Node states are continuous
2. Increase δ and neighborhood size $|\mathcal{N}|$
   $\Rightarrow$ synchronization

But for contagion model:

1. Node states are binary
2. Asynchrony remains as connectivity increases

Chaotic behavior in coupled systems

Coupled maps are well explored (Kaneko/Kuramoto):

$$x_{i,n+1} = f(x_{i,n}) + \sum_{j \in \mathcal{N}_i} \delta_{i,j} f(x_{j,n})$$

- $\mathcal{N}_i$ = neighborhood of node i

1. Node states are continuous
2. Increase δ and neighborhood size $|\mathcal{N}|$ $\Rightarrow$ synchronization

But for contagion model:

1. Node states are binary
2. Asynchrony remains as connectivity increases

Chaotic behavior in coupled systems

Coupled maps are well explored (Kaneko/Kuramoto):

$$x_{i,n+1} = f(x_{i,n}) + \sum_{j \in \mathcal{N}_i} \delta_{i,j} f(x_{j,n})$$

- $\mathcal{N}_i$ = neighborhood of node i

1. Node states are continuous
2. Increase δ and neighborhood size $|\mathcal{N}|$

$\Rightarrow$ synchronization

But for contagion model:

1. Node states are binary
2. Asynchrony remains as connectivity increases

Chaotic behavior in coupled systems

Coupled maps are well explored (Kaneko/Kuramoto):

$$x_{i,n+1} = f(x_{i,n}) + \sum_{j \in \mathcal{N}_i} \delta_{i,j} f(x_{j,n})$$

- $\mathcal{N}_i$ = neighborhood of node i

1. Node states are continuous
2. Increase δ and neighborhood size $|\mathcal{N}|$
   $\Rightarrow$ synchronization

But for contagion model:

1. Node states are binary
2. Asynchrony remains as connectivity increases

Chaotic behavior in coupled systems

Coupled maps are well explored (Kaneko/Kuramoto):

$$x_{i,n+1} = f(x_{i,n}) + \sum_{j \in \mathcal{N}_i} \delta_{i,j} f(x_{j,n})$$

- $\mathcal{N}_i$ = neighborhood of node i

1. Node states are continuous
2. Increase δ and neighborhood size $|\mathcal{N}|$

$\Rightarrow$ synchronization

But for contagion model:

1. Node states are binary
2. Asynchrony remains as connectivity increases

Chaotic behavior in coupled systems

Coupled maps are well explored (Kaneko/Kuramoto):

$$x_{i,n+1} = f(x_{i,n}) + \sum_{j \in \mathcal{N}_i} \delta_{i,j} f(x_{j,n})$$

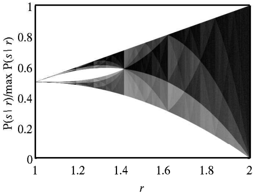
- $\mathcal{N}_i$ = neighborhood of node i

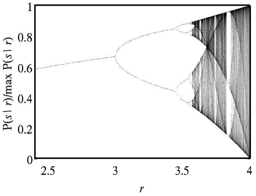
1. Node states are continuous
2. Increase δ and neighborhood size $|\mathcal{N}|$
   $\Rightarrow$ synchronization

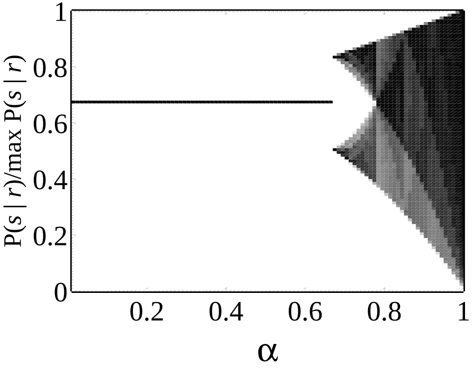
But for contagion model:

1. Node states are binary
2. Asynchrony remains as connectivity increases

Bifurcation diagram: Asynchronous updating







References I

S. Bikhchandani, D. Hirshleifer, and I. Welch.
A theory of fads, fashion, custom, and cultural change as informational cascades.
J. Polit. Econ., 100:992–1026, 1992.

S. Bikhchandani, D. Hirshleifer, and I. Welch.
Learning from the behavior of others: Conformity, fads, and informational cascades.
J. Econ. Perspect., 12(3):151–170, 1998. pdf (⊞)

J. Carlson and J. Doyle.
Highly optimized tolerance: A mechanism for power laws in design systems.
Phys. Rev. Lett., 60(2):1412–1427, 1999. pdf (⊞)

References II

J. Carlson and J. Doyle.
Highly optimized tolerance: Robustness and design in complex systems.
Phys. Rev. Lett., 84(11):2529–2532, 2000. pdf (⊞)

N. A. Christakis and J. H. Fowler.
The spread of obesity in a large social network over 32 years.
New England Journal of Medicine, 357:370–379, 2007. pdf (⊞)

N. A. Christakis and J. H. Fowler.
The collective dynamics of smoking in a large social network.
New England Journal of Medicine, 358:2249–2258, 2008. pdf (⊞)

References III

R. B. Cialdini.
Influence: Science and Practice.
Allyn and Bacon, Boston, MA, 4th edition, 2000.

M. Gladwell.
The Tipping Point.
Little, Brown and Company, New York, 2000.

M. Granovetter.
Threshold models of collective behavior.
Am. J. Sociol., 83(6):1420–1443, 1978. pdf (⊞)

M. Granovetter and R. Soong.
Threshold models of diversity: Chinese restaurants, residential segregation, and the spiral of silence.
Sociological Methodology, 18:69–104, 1988. pdf (⊞)

References IV

M. S. Granovetter and R. Soong.
Threshold models of interpersonal effects in consumer demand.
Journal of Economic Behavior & Organization, 7:83–99, 1986.
Formulates threshold as function of price, and introduces exogenous supply curve. pdf (⊞)

E. Katz and P. F. Lazarsfeld.
Personal Influence.
The Free Press, New York, 1955.

T. Kuran.
Now out of never: The element of surprise in the east european revolution of 1989.
World Politics, 44:7–48, 1991.

References V

T. Kuran.
Private Truths, Public Lies: The Social Consequences of Preference Falsification.
Harvard University Press, Cambridge, MA, Reprint edition, 1997.

T. Schelling.
Dynamic models of segregation.
J. Math. Sociol., 1:143–186, 1971.

T. C. Schelling.
Hockey helmets, concealed weapons, and daylight saving: A study of binary choices with externalities.
J. Conflict Resolut., 17:381–428, 1973.

T. C. Schelling.
Micromotives and Macrobehavior.
Norton, New York, 1978.

References VI

D. Sornette.
Critical Phenomena in Natural Sciences.
Springer-Verlag, Berlin, 2nd edition, 2003.

D. J. Watts.
A simple model of global cascades on random networks.
Proc. Natl. Acad. Sci., 99(9):5766–5771, 2002.
pdf (⊞)

U. Wilensky.
Netlogo segregation model.
`http://ccl.northwestern.edu/netlogo/models/Segregation`. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL., 1998.