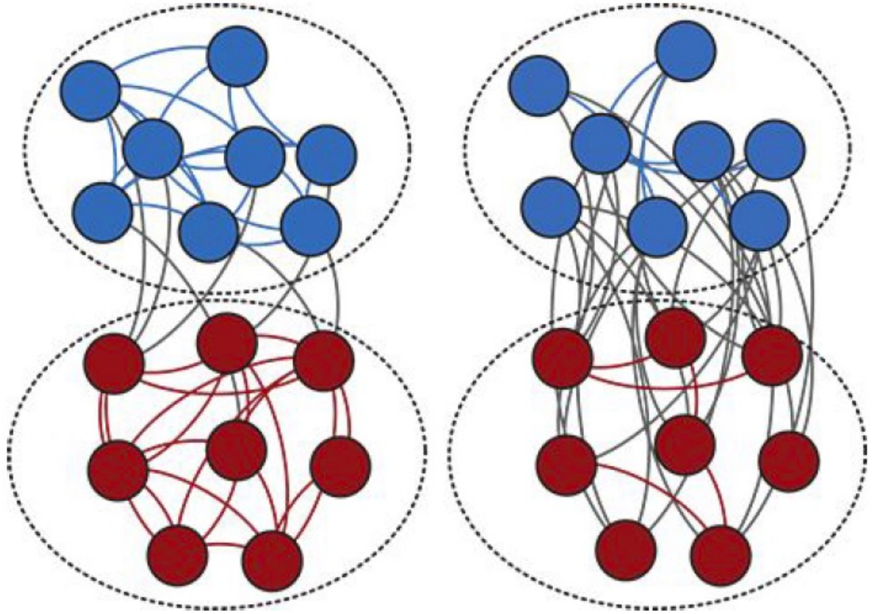
Network Analysis

AN INTRODUCTION FOR HUMANISTS

Dr Katarzyna Anna Kapitan
3 April 2025

Recap

- Random Graphs & Network Models (Week 6)
- Community Detection & Modularity (Week 7)
- Today: Network Dynamics



Network modularity (left – real, right – the same but randomized)
Image source: Menczer (2020), based on Fortunato and Hric (2016).

By County, Time-Lapse Spread of COVID-19 Map (Cumulative)

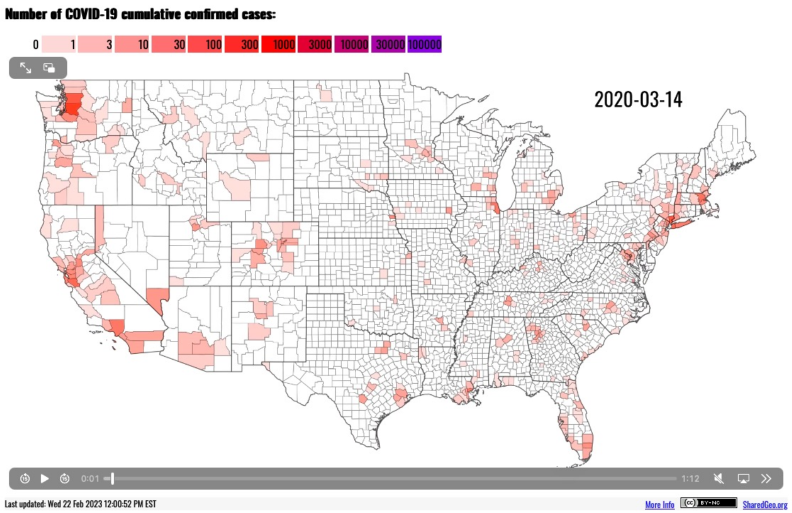
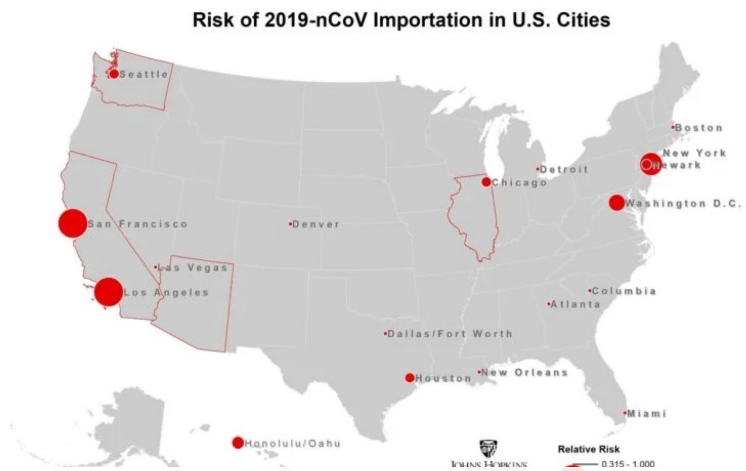


Image Source: https://www.sharedgeo.org/COVID-19/



Modeling the Spreading Risk of 2019-nCoV. Image Source (31 January 2020) https://systems.jhu.edu/research/public-health/ncov-model-2/, based on modelling in: https://www.nature.com/articles/s41598-019-38665-w

Figure 4. Map of highest risk U.S. cities based on likelihood of 2019-nCoV arriving travelers

> Viruses. 2022 Aug 22;14(8):1840. doi: 10.3390/v14081840.

COVID-19 Modeling Outcome versus Reality in Sweden

Marcus Carlsson [1], Cecilia Söderberg-Nauclér [2 3 4]

Affiliations + expand

PMID: 36016462 PMCID: PMC9415753 DOI: 10.3390/v14081840

Abstract

It has been very difficult to predict the development of the COVID-19 pandemic based mathematical models for the spread of infectious diseases, and due to major non-pha interventions (NPIs), it is still unclear to what extent the models would have fit reality i nothing" scenario. To shed light on this question, the case of Sweden during the time autumn 2020 to spring 2021 is particularly interesting, since the NPIs were relatively n marginally updated. We found that state of the art models are significantly overestima

Epidemiol Infect. 2020 Oct 8;148:e249. doi: 10.1017/S0950268820002423

A predictive model for Covid-19 spread – with application to eight US states and how to end the pandemic

Z S Khan [1], F Van Bussel [1], F Hussain [1,*]

Author information Article notes Copyright and License information

PMCID: PMC7588724 PMID: 33028445

Abstract

A compartmental model is proposed to predict the coronavirus 2019 (Covid-19) spread. It considers: detected and undetected infected populations, social sequestration, release from sequestration, plus reinfection. This model, consisting of seven coupled equations, has eight coefficients which are evaluated by fitting data for eight US states that make up 43% of the US population. The evolution of Covid-19 is fairly similar among the states: variations in contact and undetected recovery rates remain below 5%; however, variations are larger in

nature > scientific reports > articles > article

Article | Open access | Published: 18 February 2019

A decision-support framework to optimize border control for global outbreak mitigation

Aleksa Zlojutro, David Rey & Lauren Gardner

Scientific Reports 9, Article number: 2216 (2019) | Cite this article

Abstract

The introduction and spread of emerging infectious diseases is increasing in both prevalence and scale. Whether naturally, accidentally or maliciously introduced, the substantial uncertainty surrounding the emergence of novel viruses, specifically where they may come from and how they will spread, demands robust and quantifiably validated outbreak control policies that can be implemented in real time. This work presents a novel mathematical

Viruses. 2023 Aug 23;15(9):1788. doi: 10.3390/v15091788

Mathematical Modelling of Virus Spreading in COVID-19

Liaofu Luo [1,*], Jun Lv [2,*]

Editor: Hernan Garcia-Ruiz

Author information Article notes Copyright and License information

PMCID: PMC10537511 PMID: 37766195

Abstract

A mathematical model is proposed to analyze the spreading dynamics of COVID-19. By using the parameters of the model, namely the basic reproduction number (R_0) and the attenuation constant (k), the daily number of infections (DNI) and the cumulative number of infections (CNI) over time (m) are deduced and shown to be in good agreement with experimental data. This model effectively addresses three key issues: (1) inferring the conditions under which virus infections die out for a specific strain given R_0; (2) explaining the occurrence of second waves of infection and developing preventive measures; and (3)

Dynamics

- **We study dynamic networks to learn**
- **what happens on the network over time, e.g.:**
  - How information and diseases are transmitted across links
  - How node attributes are affected by the interactions between nodes
  - How the structure of the network changes based on the dynamic processes taking place on the network

Dynamics

- Epidemic spreading
- Information diffusion
- Opinion dynamics

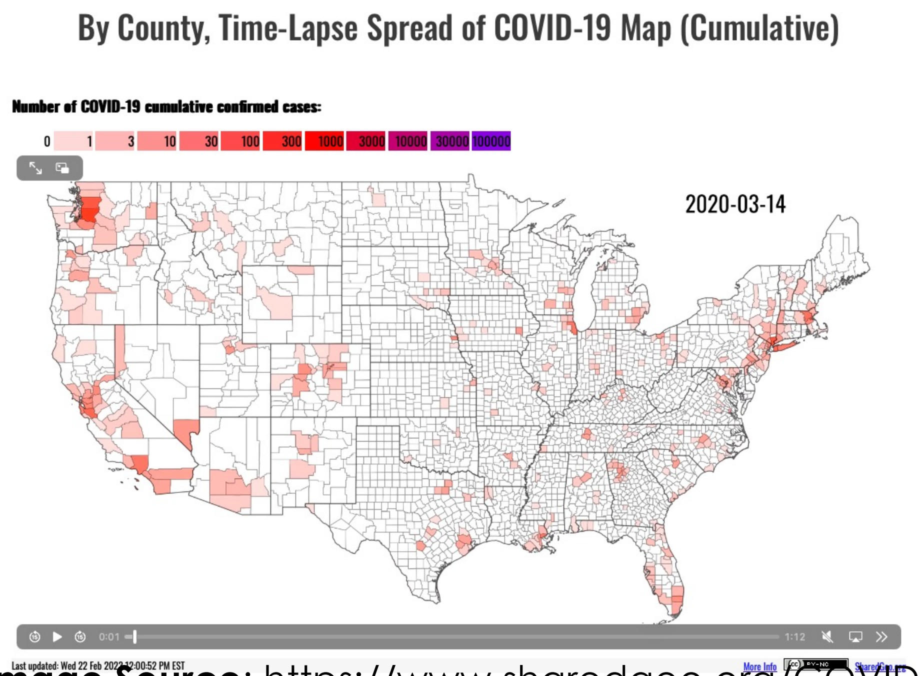
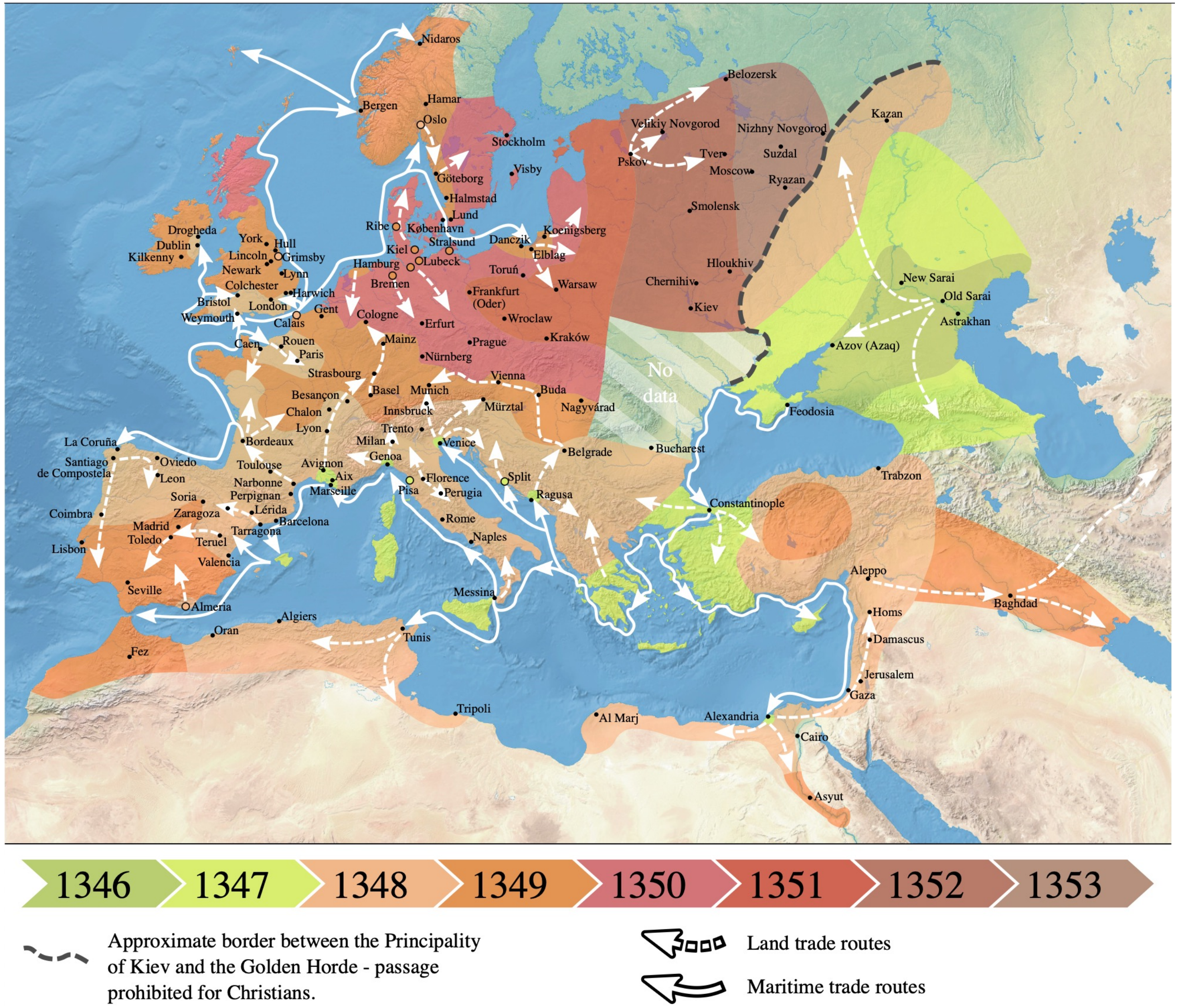


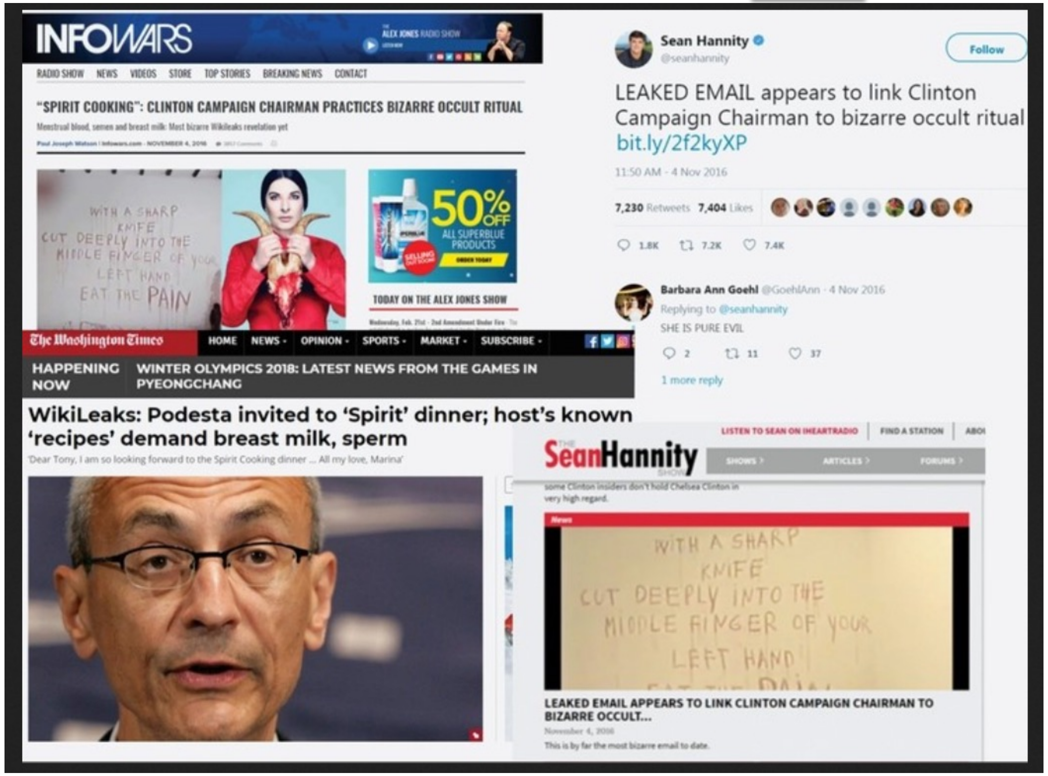
Image Source: https://www.sharedgeo.org/COVID-19/



The spread of the Black Death in 14th cent Europe. Image source: Menczer et al., *A First Course…* (2020), based on Cesana,, Benedictow, Bianucci (2017). "The origin and early spread of the Black Death in Italy: first evidence of plague victims from 14th-century Liguria (northern Italy)". DOI: 10.1537/ase.161011.

Fake News, Poetry, and Politics

- Days before the **2016** US presidential elections
- Emails containing a note from **Marina Abramovic** to **Tony Podesta**, about **Spirit Cooking** published on **Wikileaks**
- Tony Podesta is brother of **John Podesta**
- John Podesta was a chairman of **Hillary Clinton**'s presidential campaign
- **Clinton** and **Podesta** get linked to the **occult and Satan** worshipping from the alt-right.

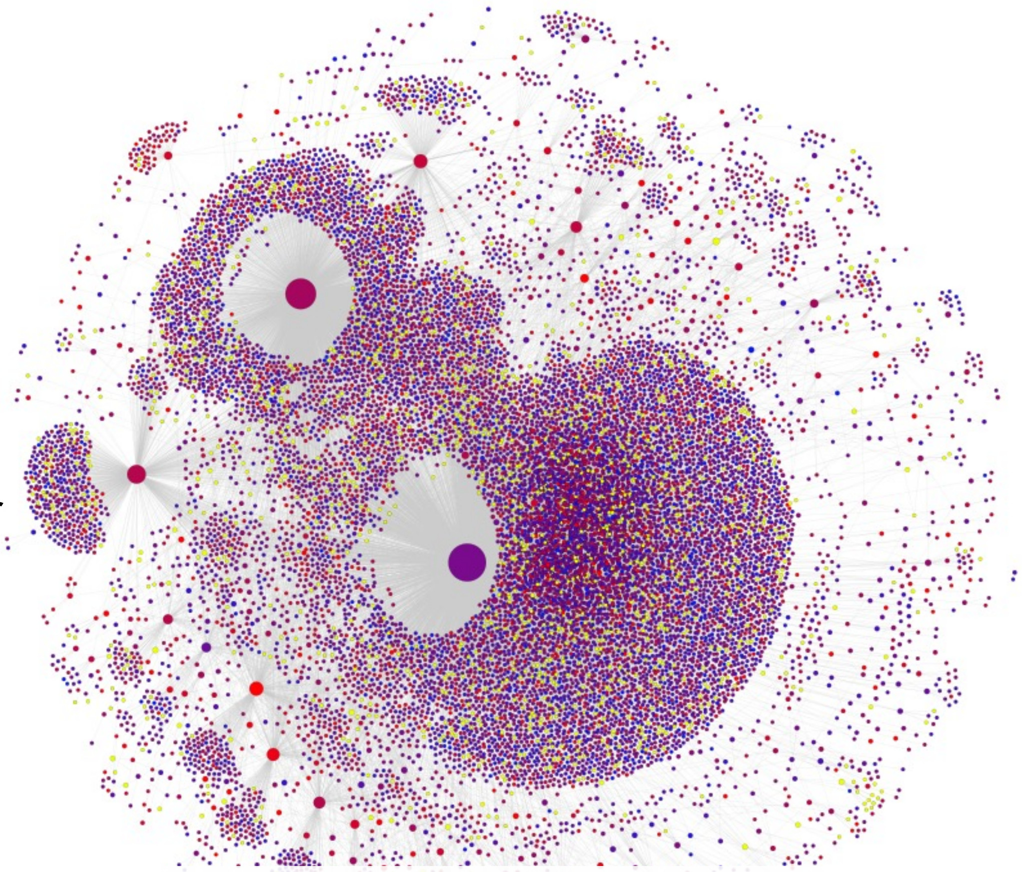


'Spirit cooking' media coverage. 2016 Image source: Benkler et a;., 'The Propaganda Pipeline: Hacking the Core from the Periphery', *Network Propaganda: Manipulation, Disinformation, and Radicalization in American Politics*. DOI: https://doi.org/10.1093/oso/9780190923624.003.0007.

Bots as Influencers

14.000.000 messages
spreading 400.000 articles on Twitter
during ten months in 2016 and 2017

Red nodes are likely bots



Core of the diffusion network of a viral fabricated news report of InfoWars in 2016. Image source: Menczer et al., *A First Course*… (2020), based on Shao et al., 'The spread of low-credibility content by social bots'(https://www.nature.com/articles/s41467-018-06930-7). See also: https://github.com/osome-iu/HoaxyBots

Exercise (10 min)

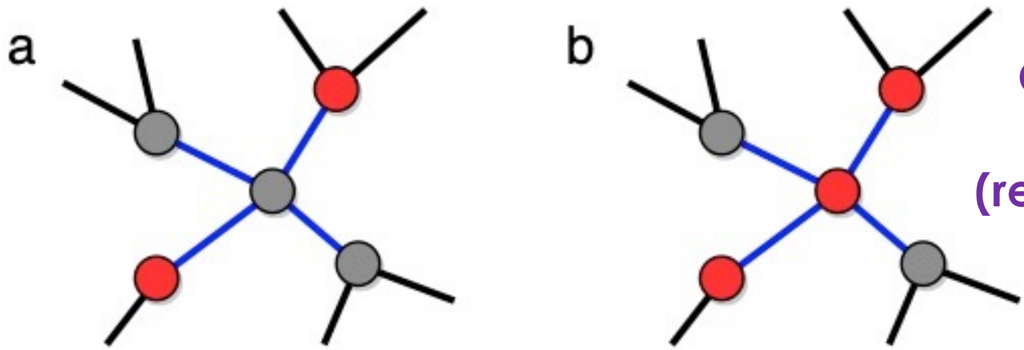
- Go to **Hoaxy2** & choose BlueSky as the platform
- Choose a term that is interesting to you, e.g. “digital humanities”
- choose a timeframe (not longer than from the beginning of 2025 as it is sloooooow)
- Examine the visualisation
- Prepare a short presentation of the story of this concept on BlueSky, answering the following questions:
  - who are they key players?
  - how did the network change over time?
  - Why & how is the visualisation useful?

Hoaxy2: Interactive visualisation tool to visualise the spread of information on social media.

See: https://hoaxy.osome.iu.edu

Modelling Influence & Diffusion: Threshold Models

Peer pressure –> the more of our contacts share an idea or own a product, the more likely it is that we will adopt it ourselves.



Colours represent different attributes, for example, car ownership (red nodes have a car, grey ones don't). What happened to the central node between state a and b?

Modelling Influence & Diffusion: Threshold Models

$$I(i) = \sum_{j:\text{active}} w_{ji}.$$

I(i) - Influence on node *i* is defined as the sum of the weights of active neighbours.

$$I(i) \geq \theta_i,$$

Condition for activation of node *i*: The Influence on node *i* (*I*) *has to be equal or greater than the threshold of the node* (θ).

- **Linear threshold model:**
  - the influence on a node is defined as a sum over its active neighbours and the weight of connections
  - the stronger the connection between the nodes, the higher influence of the neighbours

$$n_i^{on} \geq \theta_i.$$

In unweighted network, the number of active nodes n_i^{on} has to be equal to or higher than the threshold.

Source: Menczer et al., *A First Course…* (2020).

Threshold Models

- Each iteration of a threshold model consists of the following:
  - All active nodes remain active
  - Each inactive node is activated if the number of active neighbours is at or above the threshold.

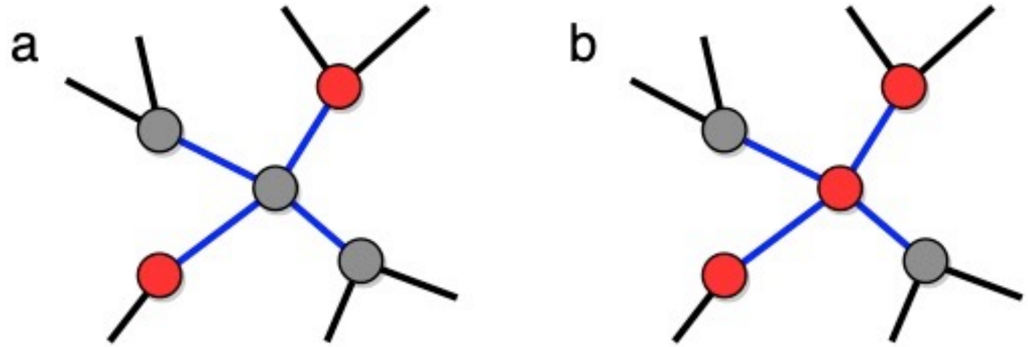
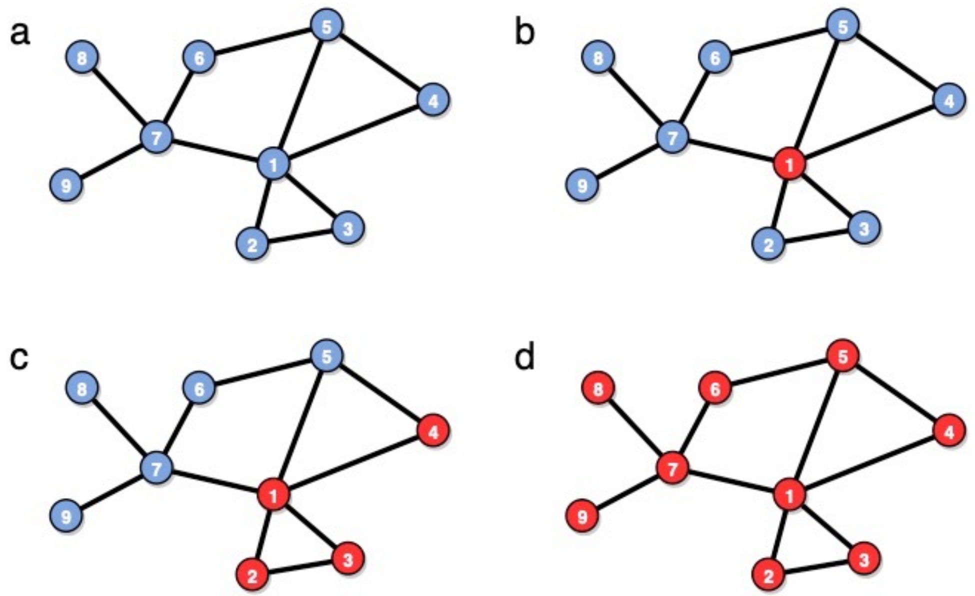


Image source: Menczer et al., *A First Course…* (2020).

Fractional Threshold Model



Source: Menczer et al., *A First Course…* (2020).

Activation threshold is ½ for all nodes.

a) No one has a car
b) Node 1 gets a car
c) Nodes 2, 3, and 4 get a car, as for each of them node 1 is >= ½ of all their neighbours.
d) All nodes get a car.

What if the initial node was 7 and the threshold would remain ½.
Would all nodes in the network get a car?
If no, which nodes wouldn't and why?

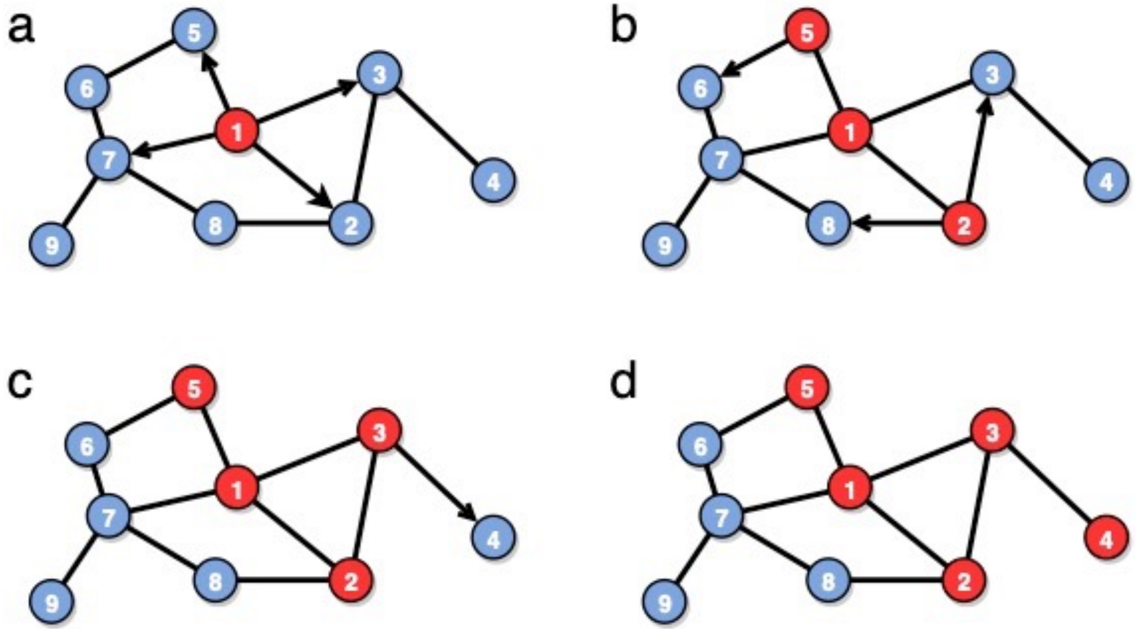
Independent cascade model

Peer-pressure explains a lot of processes, but, for example, social influence is often one-to-one, for example, we may buy a car if a single friend speaks enthusiastically about it.

In the spread of information on SoMe, we might share misinformation if we trust the source.

In independent cascade models each node is activated with some influence probability. The higher the number of active neighbours of an inactive target node, the larger the number of attempts to influence the node, and the more likely that it will get activated.

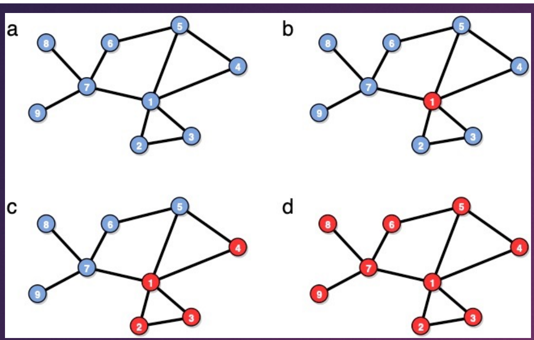
Independent cascade model

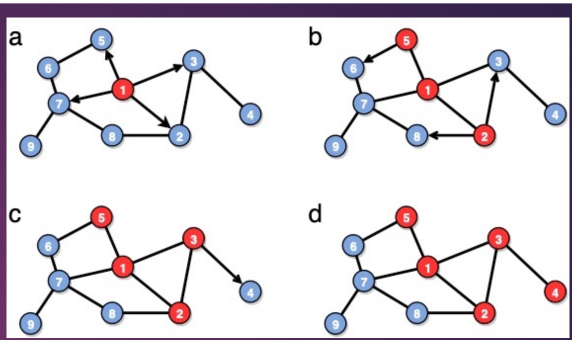


Source: Menczer et al., *A First Course…* (2020).

The influence probability is set to ½ for all pairs. The arrows indicate who is trying to influence whom.

a) Node 1 is trying to convince its neighbours (2, 3, 5, 7) to buy a car.
b) Node 1 succeeded to convince 2 and 5 so they buy a car & try to influence their neighbours (2 tries to influence 3 and 8, while 5 tries to influence 6).
c) Node 2 succeeds in convincing node 3, but not 8, while node 5 doesn't succeed in convincing 6.
d) Node 3 succeeds in convincing node 4 to buy a car.





Threshold models are centred on the **target**, who is activated if the threshold condition is satisfied.

Independent cascade models are centred on the **influencer**, who persuades its inactive neighbours with given probabilities.

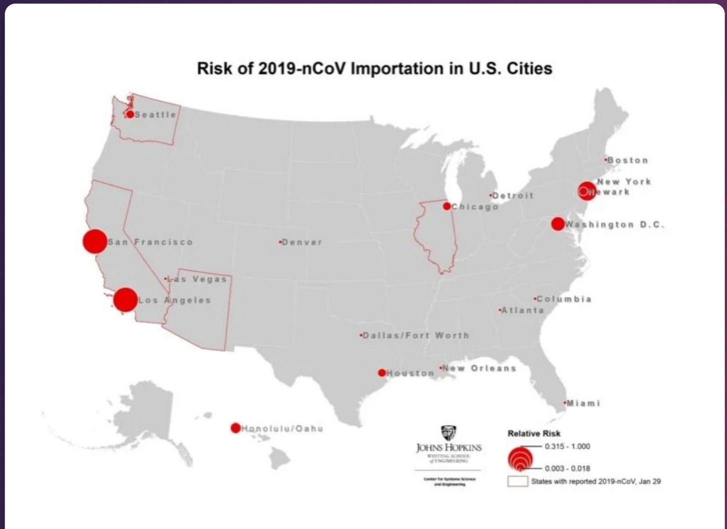
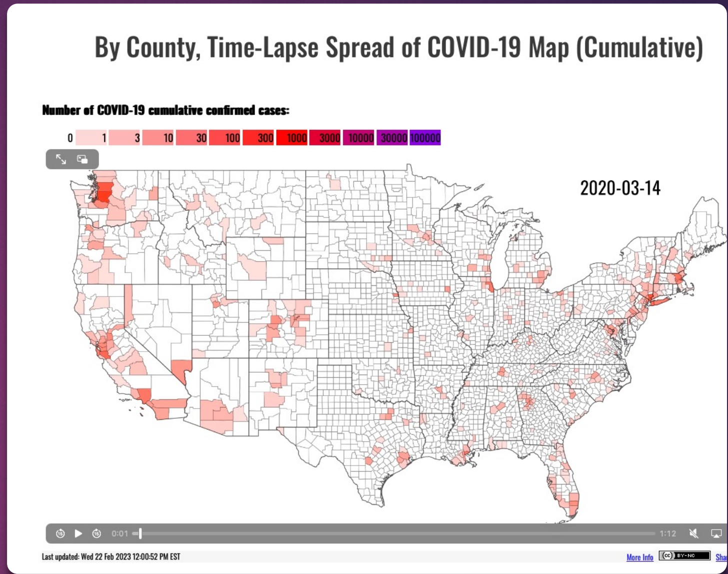
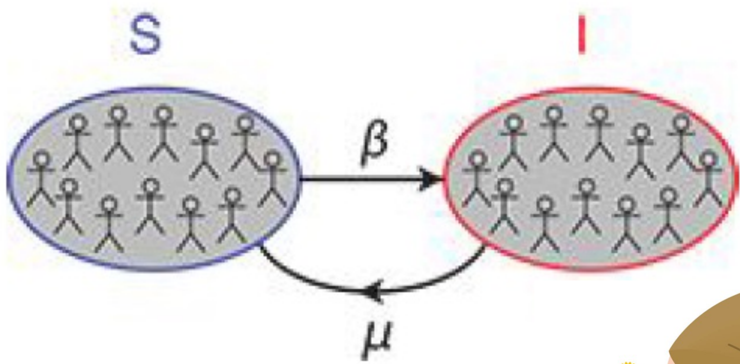


Figure 4. Map of highest risk U.S. cities based on likelihood of 2019-nCoV arriving travelers



Disease Spreading

Epidemic Spreading: SIS model



S - Susceptible individuals who can contract the disease

I – Infected individuals who have already contracted and can transmit it to S

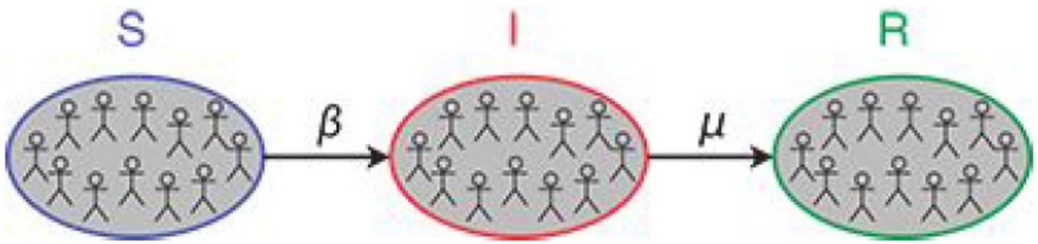
SIS model works for diseases like **common cold** that do not confer long-lasting immunity

http://clipart-library.com/clipart/14193347.htm

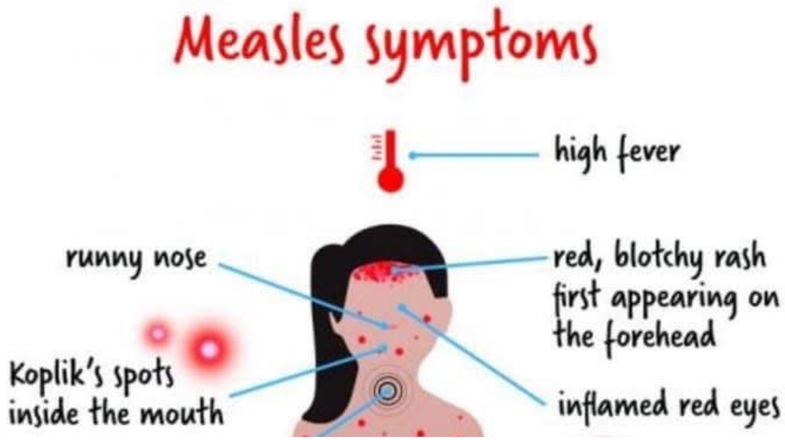
Source: Menczer et al., *A First Course…* (2020).

Epidemic Spreading: SIR model

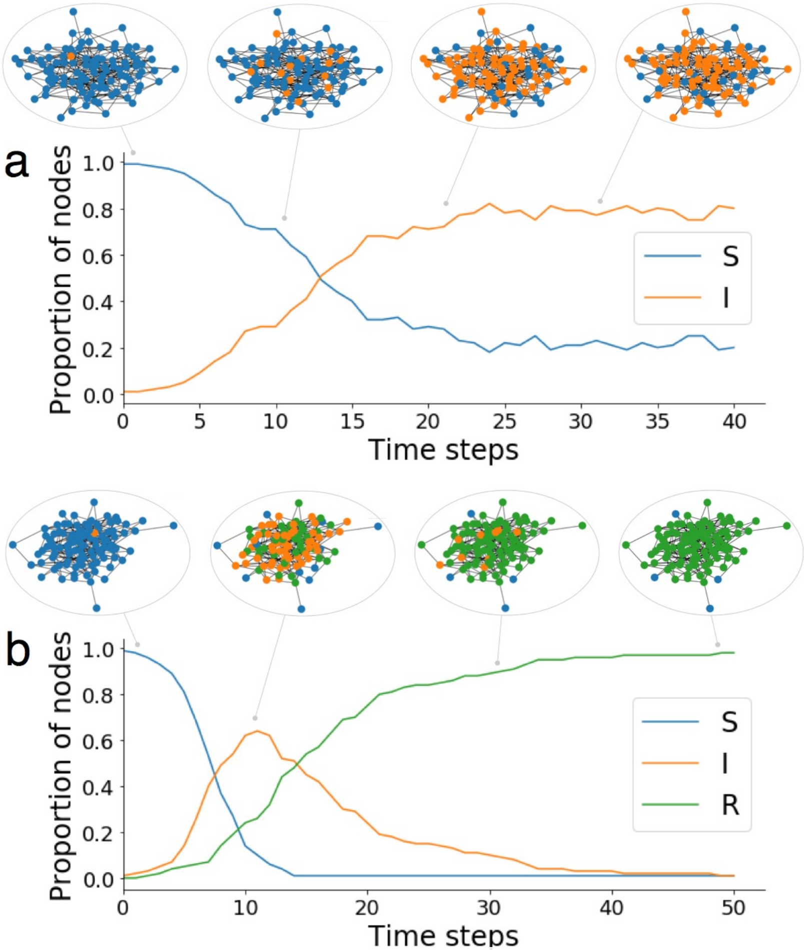
S - Susceptible individuals who can contract the disease
I – Infected individuals who have already contracted and can transmit it to S
R – Recovered individuals who confer long-lasting immunity



SIR model works for diseases like **measles** that confer long-lasting immunity

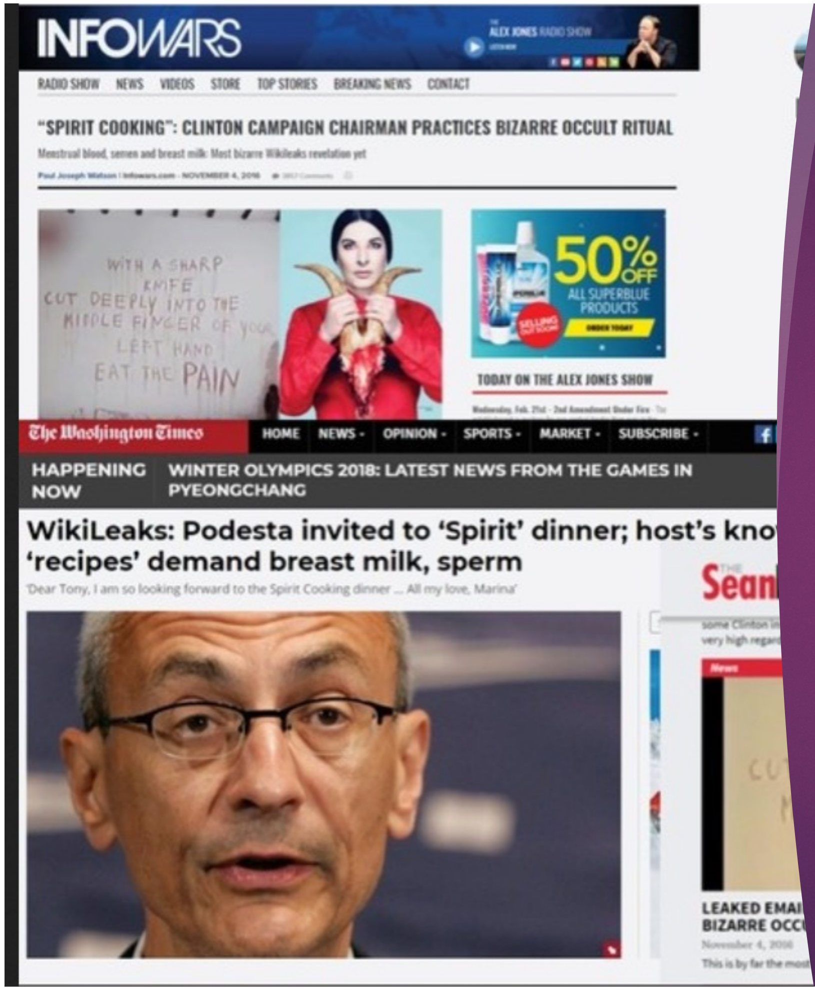


Source: Menczer et al., *A First Course…* (2020).



Source: Menczer et al., *A First Course…* (2020).

- Schematic evolution of SIS (a) and SIR (b) model dynamics.
- The fraction of infected individuals is plotted over time, following an epidemic outbreak.
- The final phase depends on the model:
  - SIS – the infected stabilize around a constant fraction – endemic state.
  - SIR – the infected fraction always goes down to zero as individuals recover

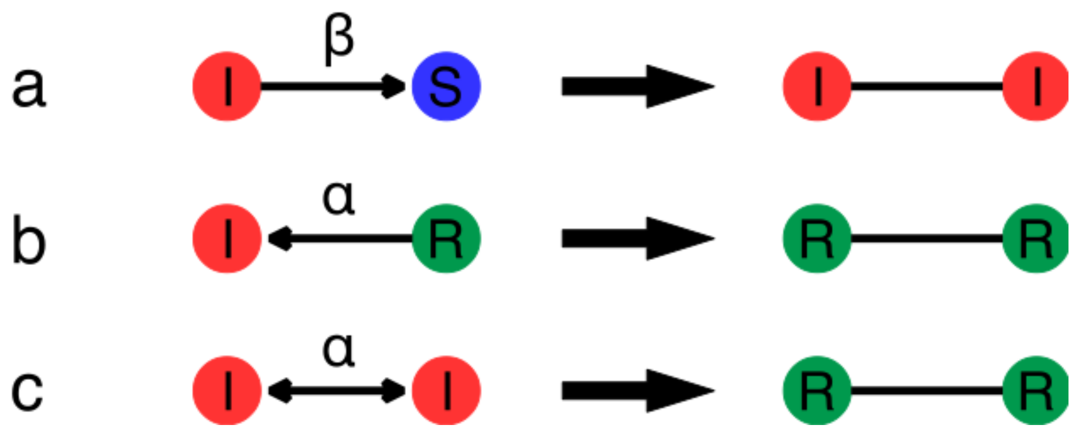


Rumour Spreading

Rumour Spreading

- **Rumour-spreading model is a variant of SIR where:**
  - **S – Susceptible individuals** are the **ignorant individuals** who don’t know about rumour but can learn about it.
  - **I – Infected individuals** are the **spreaders** who know about the rumour and choose to actively spread it.
  - **R – Recovered individuals** are the **stiflers** who know about rumour but don’t contribute to spreading it.
- The basic idea: people are engaged in the diffusion of the rumour **as long as they find people who are unaware of it**, otherwise, they lose interest and stop spreading the rumour.

Rumour Spreading



Source: Menczer et al., *A First Course…* (2020).

- Two parameters:
  - Transmission probability β
  - Stop probability α
- Nodes:
  - **S (blue) – ignorant individuals** who do not know about the rumour
  - **I (red) – spreaders** of rumours
  - **R (green) – stiflers** who know the rumour but don't spread it

Opinion Dynamics

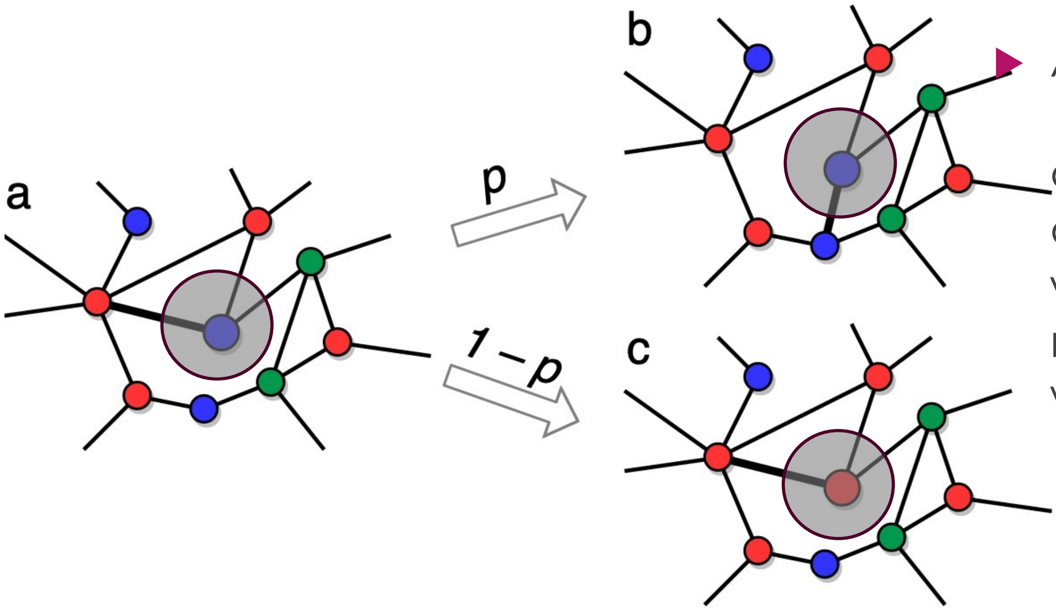
- Models of opinion dynamics are similar to models of influence spreading, but they have some distinctive features:
- An opinion can be represented as a number or a set of numbers.
- Opinion dynamics models are usually divided into two categories based on how they represent opinions:
  - Discrete (use integers to represent competing opinions), e.g. Majority Model & Voter Model
  - Continuous (real numbers), e.g. Bounded Confidence Model,

Source: Menczer et al., *A First Course…* (2020).

Coevolution of Opinions & Networks

- Fundamental question in network dynamics is ‘whether dynamics controls the structure of the network or the structure controls the dynamics”
- The network changes in response to opinion and opinion changes in response to the network
- Source: Holme & Newman (2006), ‘Nonequilibrium phase…’

Coevolution of Opinions & Networks



Source: Menczer et al., *A First Course…* (2020).

- A realistic model for opinion dynamics 'should allow for the interplay of **influence** and **selection**. This has led to the development of coevolution models, in which opinion changes may induce modifications in the network structure, which could in turn affect the opinions.'

Opinions & Networks Adapt To Each Other

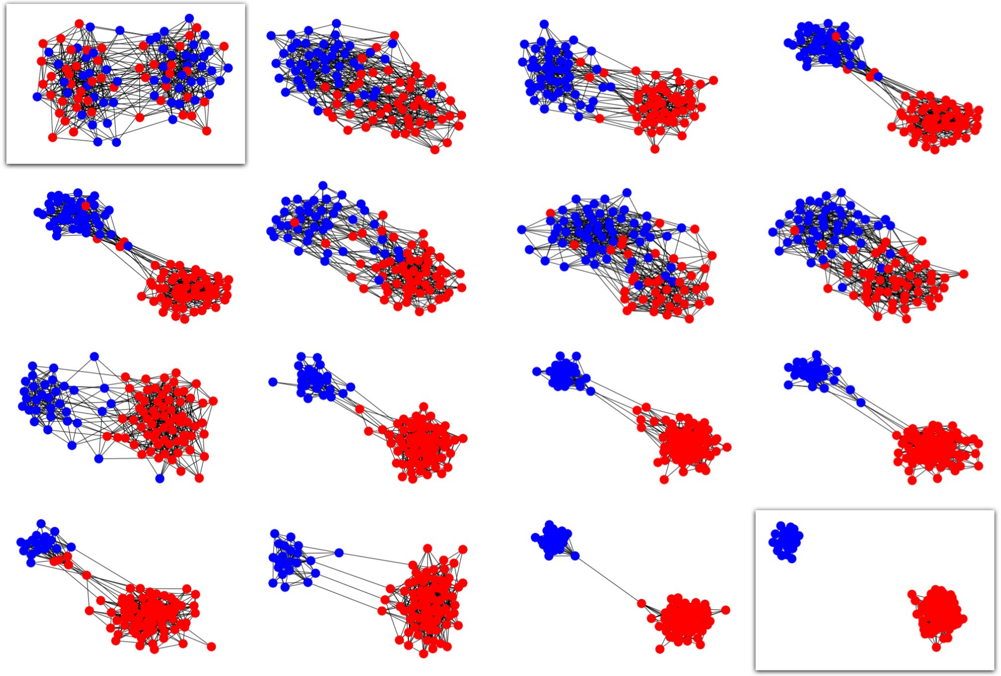
Coevolution of Opinions & Networks

Both selection and influence tend to decrease the number of neighbouring node pairs with different opinions.

The network eventually reaches a state in which all pairs of neighbours have the same opinion.

The slide illustrates the final state in which we observe a segregation into homogeneous opinion communities

This is not the only possibility!



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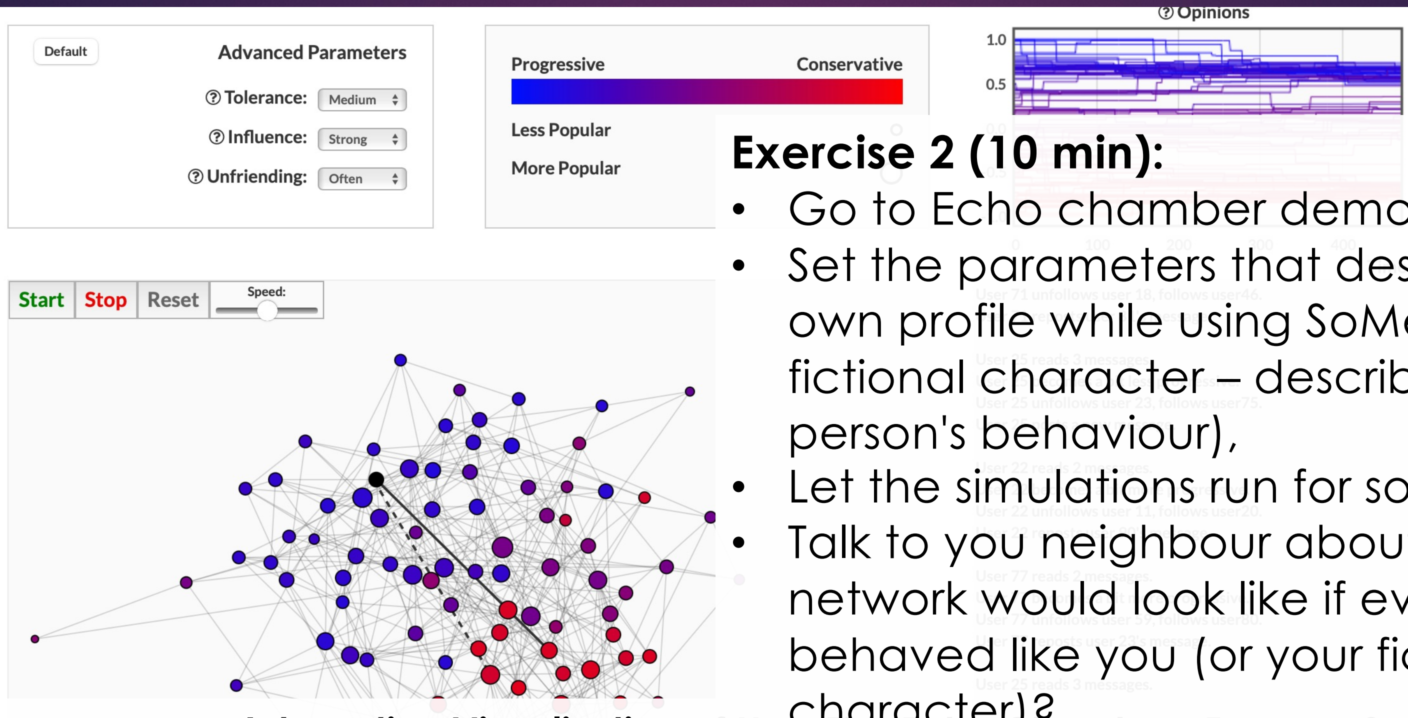


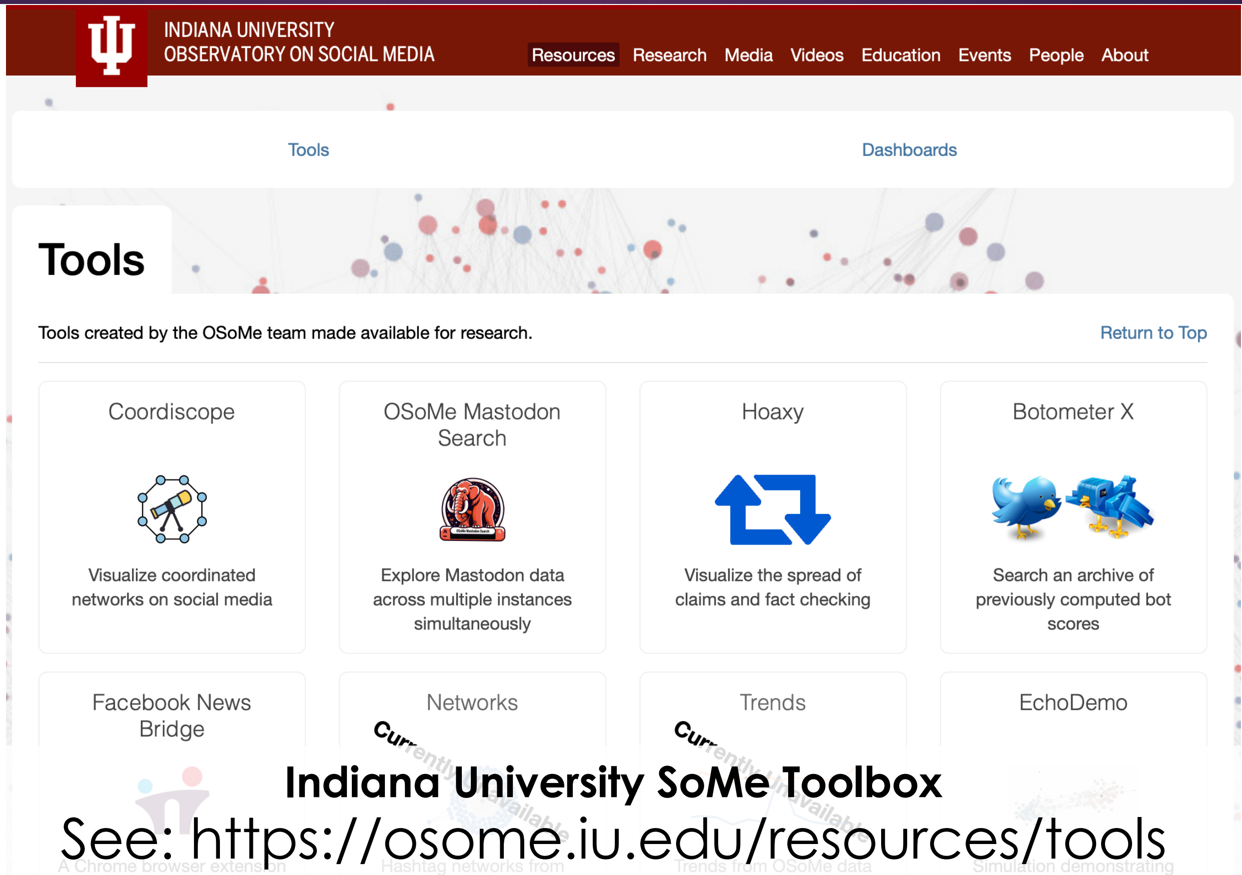
Exercise 2 (10 min):

- Go to Echo chamber demo,
- Set the parameters that describe your own profile while using SoMe (or a fictional character – describe this person's behaviour),
- Let the simulations run for some time.
- Talk to you neighbour about how the network would look like if everyone behaved like you (or your fictional character)?

Interactive Visualisation of How The Echo Chambers Form on SoMe.

See: https://osome.iu.edu/demos/echo/

based on Sasahara et al. (2020), 'Social Influence and Unfollowing Accelerate the Emergence of Echo Chambers'



Indiana University SoMe Toolbox

See: https://osome.iu.edu/resources/tools

Want to know more?

- Holme, P. and Newman, M. E. J. Nonequilibrium phase transition in the **coevolution of networks and opinions**. Phys. Rev. E 74, 056108 (2006). https://doi.org/10.1103/PhysRevE.74.056108
- Sasahara, K., Chen, W., Peng, H. et al. Social influence and unfollowing accelerate the **emergence of echo chambers**. J Comput Soc Sc 4, 381–402 (2021). https://doi.org/10.1007/s42001-020-00084-7

Feedback

https://tinyurl.com/HNNA2025