What does *who-infected-who* tell us about contagion?

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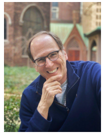
DTU

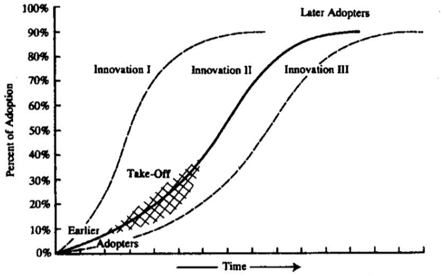
Joint with Steven Strogatz, Johan Ugander

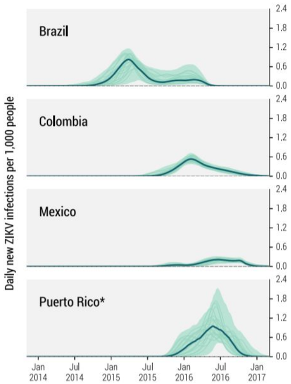


Studying who-infected-whom

Contagion is related to many important problems

- Epidemics
- Misinformation
- Bank defaults
- Memes
- …





(Rogers, 1962), (Zhang et al., 2017)

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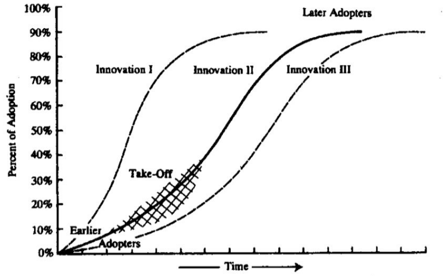

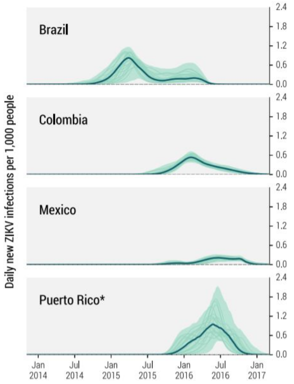

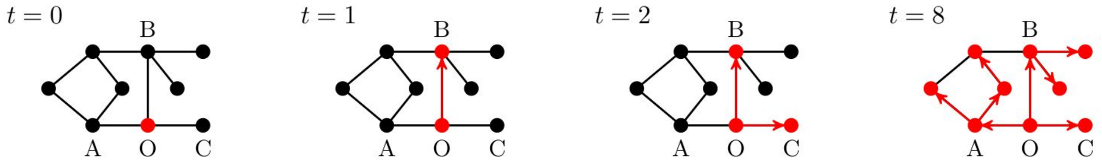

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Adoption paths (Juul&Porter, 2019)

Dissemination trees (Oh & Porter, 2019; Liben-Nowell & Kleinberg, 2008)

Spreading patterns (Jang et al., 2018)

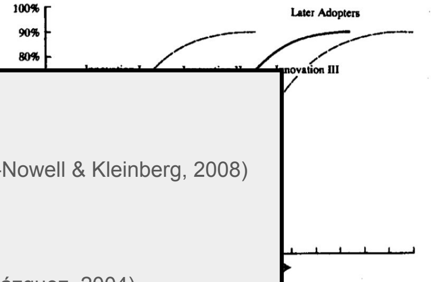
Causal tree of disease transmission (Vázquez, 2004)

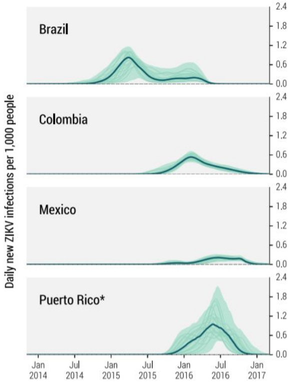
Diffusion structure patterns (Zhang et al., 2016)

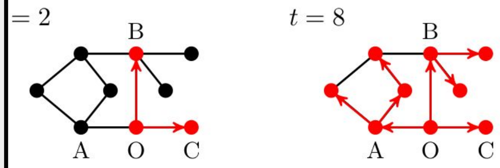
The structure of diffusion events (Goel et al., 2015)

Epidemic trees (Matthews et al., 2003)

Cascades (Vosoughi et al., 2018; Juul & Ugander, 2021)







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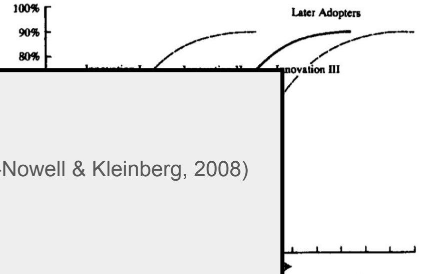

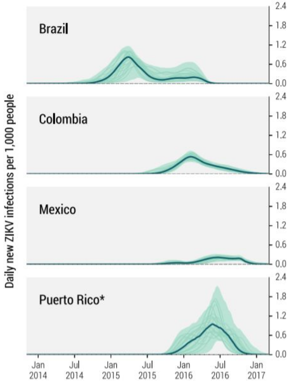

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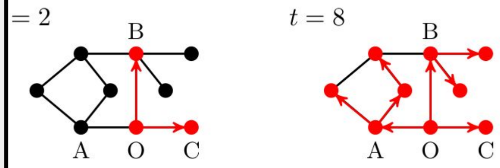


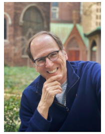
Q: What can we learn from the pattern of who-infected-whom?

(Rogers, 1962), (Zhang et al., 2017)

Mutant contagion

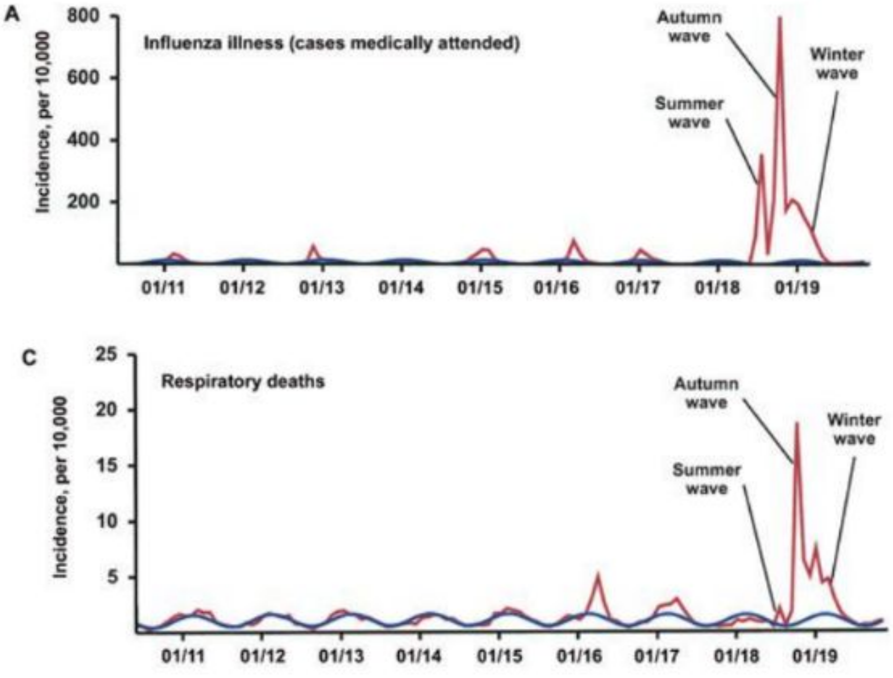
What is the expected impact of mutant disease strains?

Our study in Phys. Rev. Research: (Juul & Strogatz, 2020)



The Next Spanish Flu

- 1918: Spanish flu came in 3 waves
- One was (much) more deadly
- Summer wave gave some immunity



(Andreasen et al., 2008)

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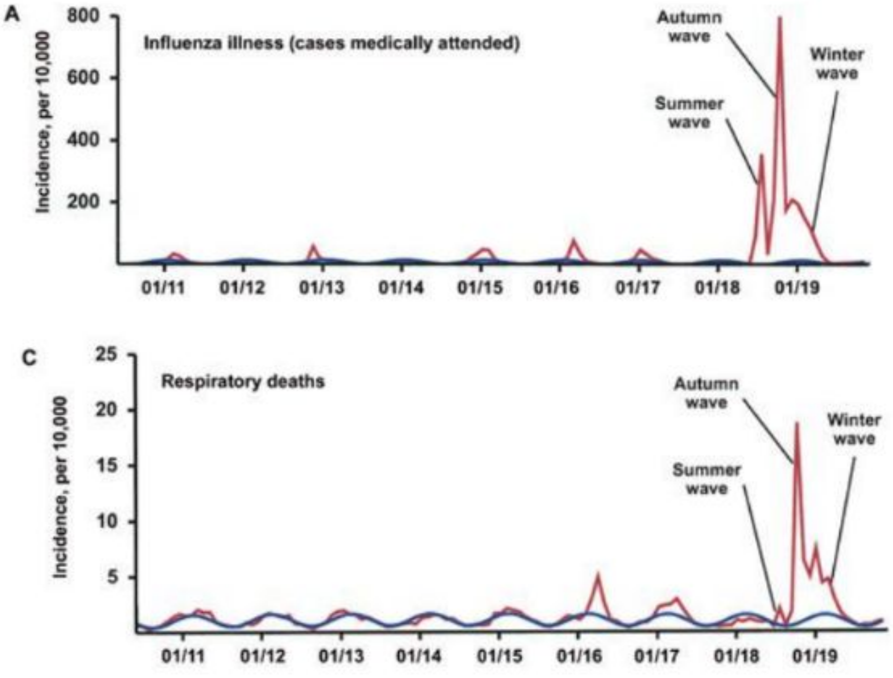

Q: How widespread would we expect a mutant strain to become?

(Andreasen et al., 2008)

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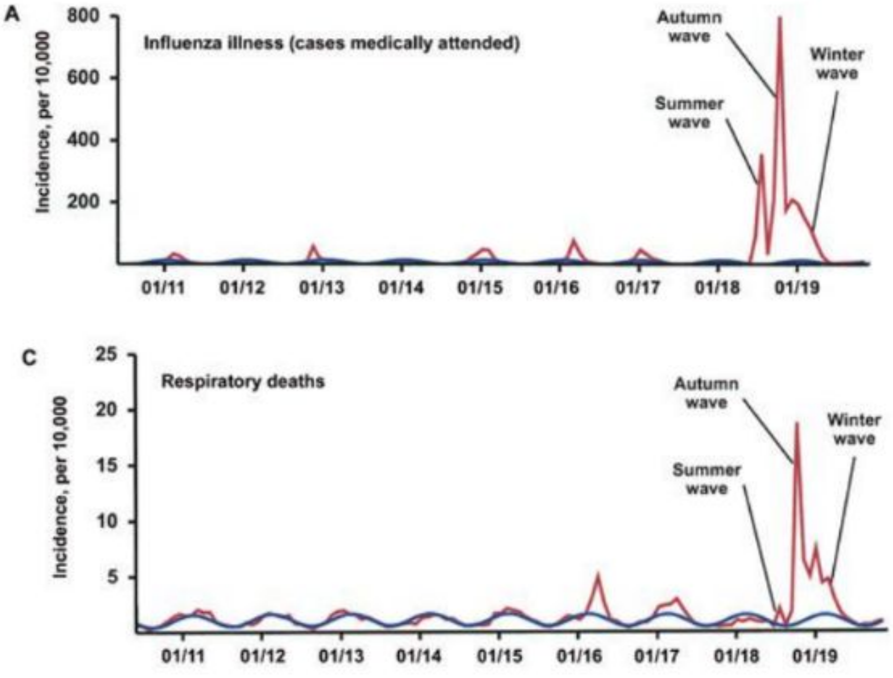
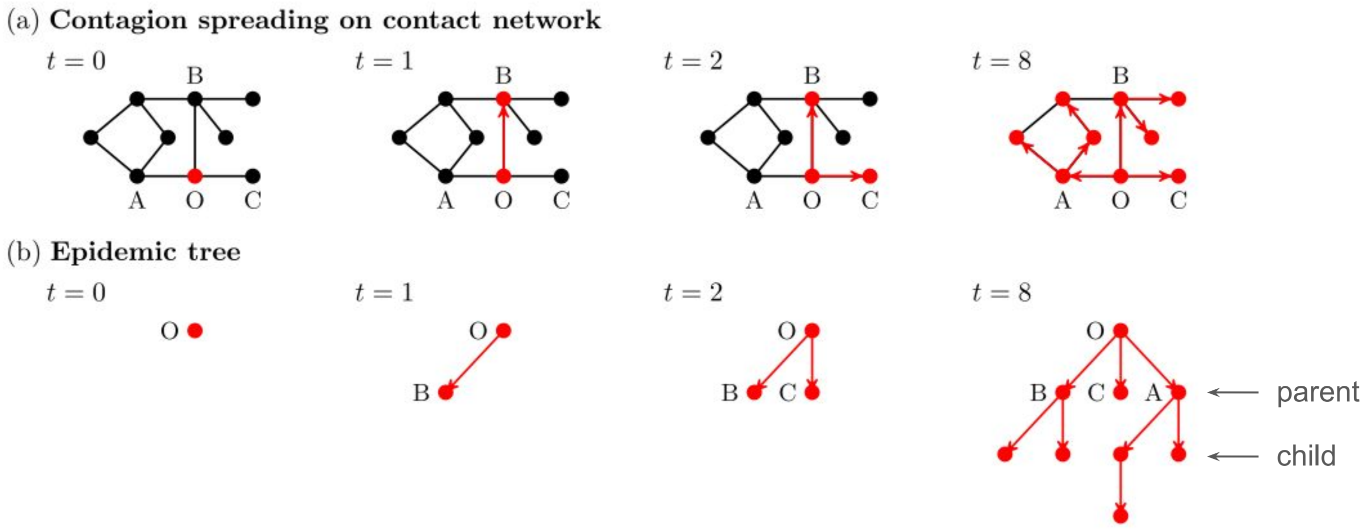


Q: How widespread would we expect a mutant strain to become?

(Our 2019 motivation: The experts say a pandemic will happen sooner or later…)

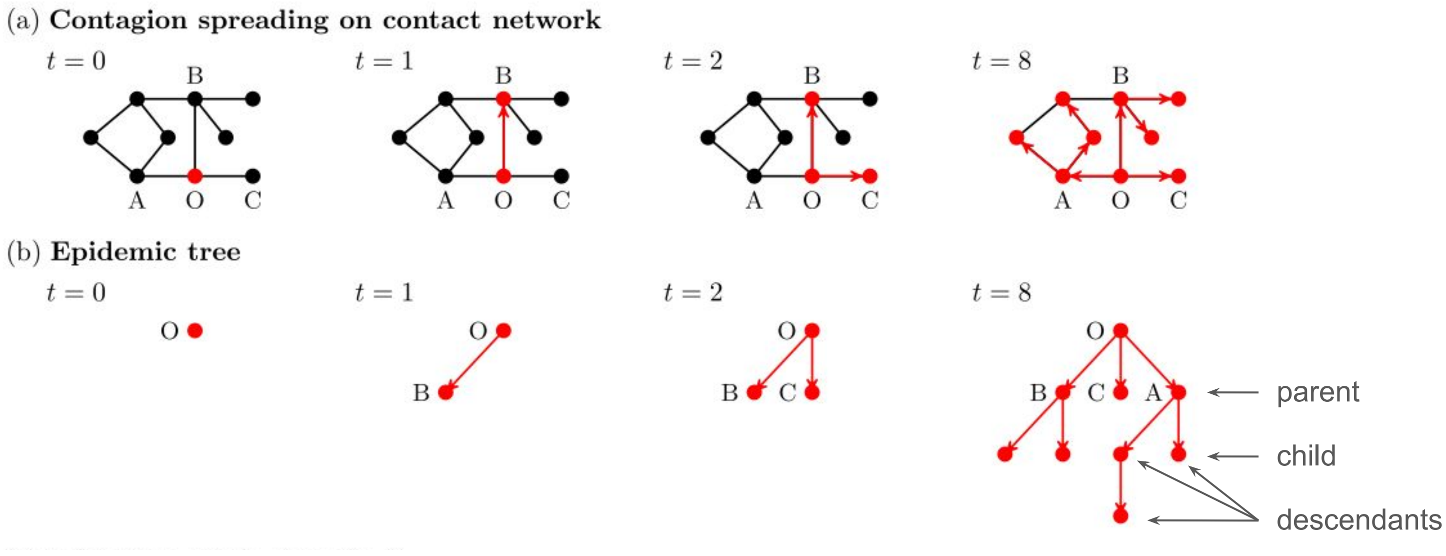
(Andreasen et al., 2008)

Descendants in epidemics

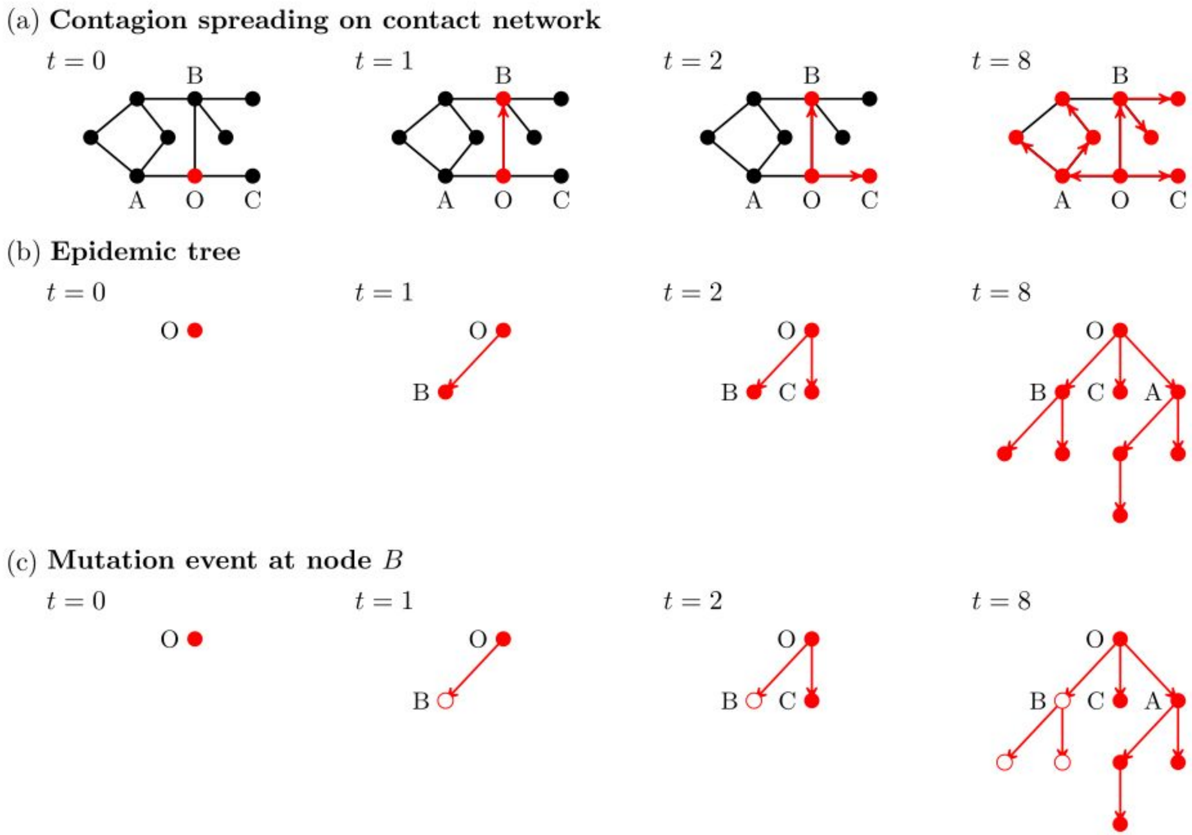


Our study: (Juul & Strogatz, 2020)

Descendants in epidemics



Descendants in epidemics



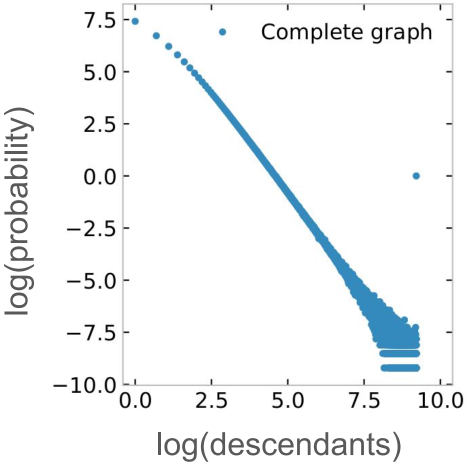
Descendants in epidemics

Q: Picking a node uniformly at random, what is the chance of it having *d* descendants?

Simulations and theory

SI model on a…

complete network



Simulations and theory

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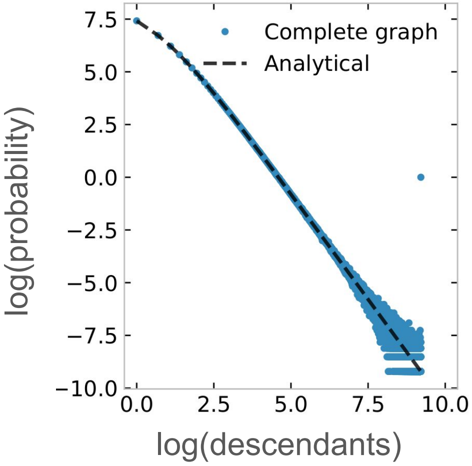

$$P_d = \frac{d!}{(d+2)!} = \frac{1}{(d+2)(d+1)}$$

Notice: $\lim_{d \to \infty} P_d \sim d^{-2}$.

See also (Krapivsky & Redner, 2005)

Simulations and theory

SI model on a…
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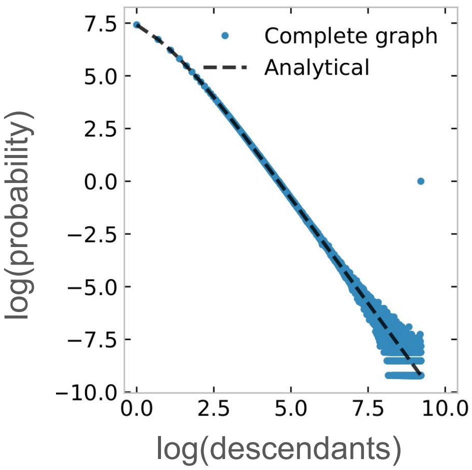
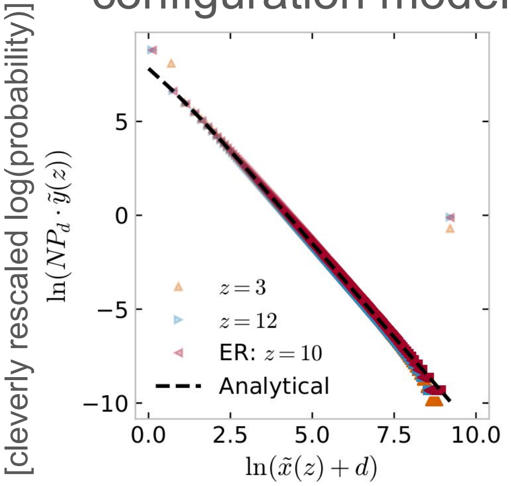


Erdös-Rényi or
configuration model



[cleverly rescaled log(descendants)]

$$P_d = B\left(\frac{z-1}{z-2} + d, 2\right)$$

Notice: $\lim_{d\to\infty} P_d \sim d^{-2}$.

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Simulations and theory

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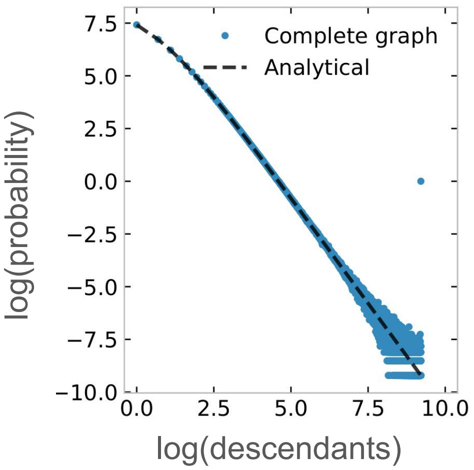

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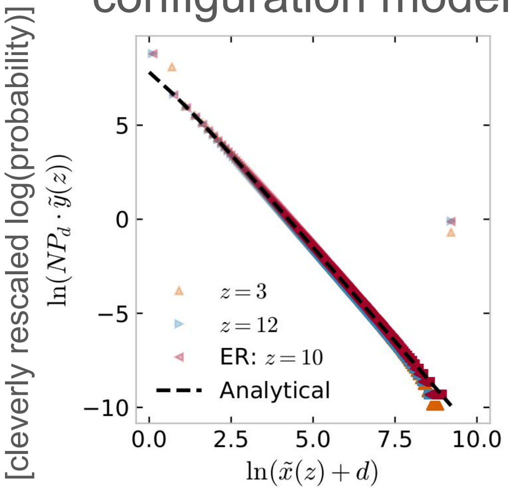

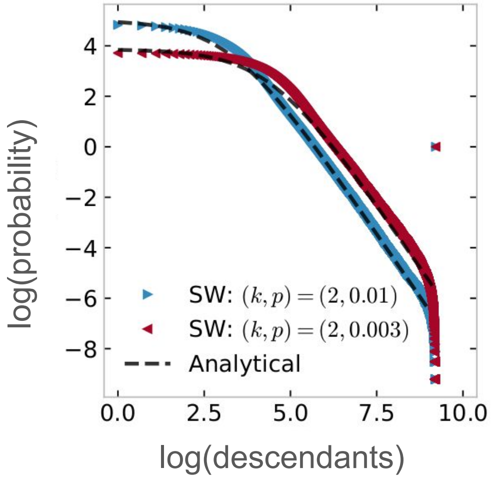

$$P_d = B\left(\frac{2p+1}{2p} + d, 2\right)$$

Notice: $\lim_{d\to\infty} P_d \sim d^{-2}$.

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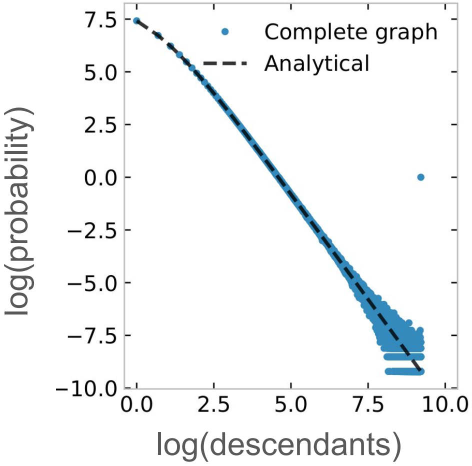

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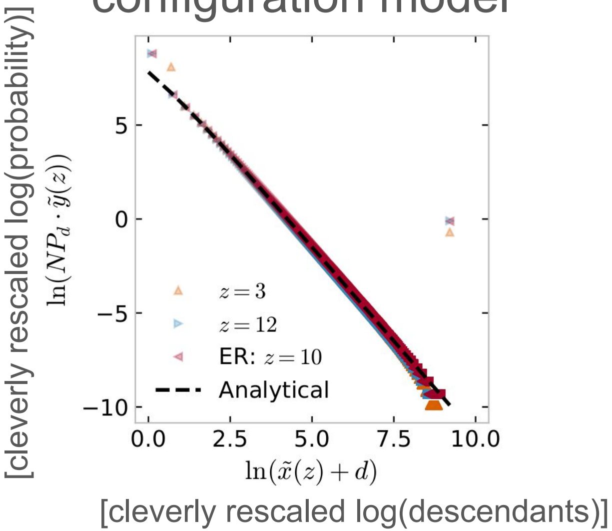

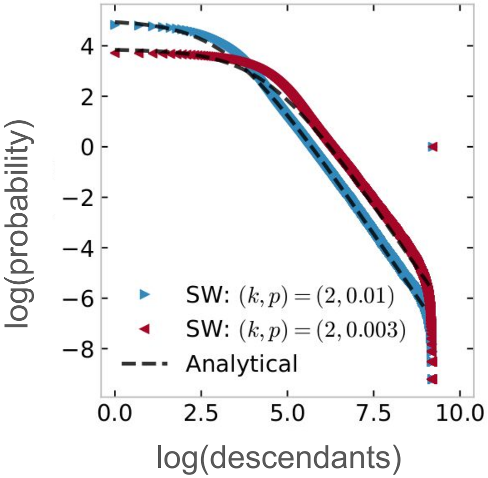

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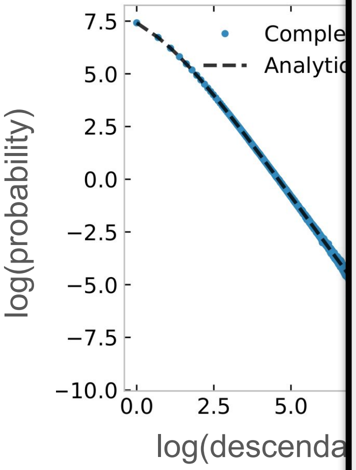
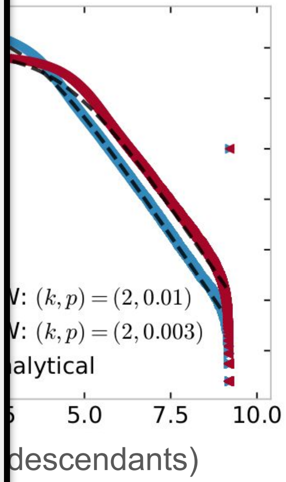


Why? Because all these networks are (effectively) infinite-dimensional… [Definition: Surface area and volume of ball grow equally fast on network.]

Bad news: A tail scaling of d^{-2} means that the mutant's expected impact diverges!

Worse news: Real-world social networks are (effectively) infinite-dimensional too.

Prediction: Same tail scaling law should exist for contagion in real-world networks.



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Mutant contagion in the real world…

Information Evolution in Social Networks

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ABSTRACT

Social networks readily transmit information, albeit with less than perfect fidelity. We present a large-scale measurement of this imperfect information copying mechanism by examining the dissem-

substrate of the network of friendship ties. While there are other environments where memes flourish, those memes that do enter Facebook can be examined in detail, uncovering mechanisms previously difficult–or impossible–to study.

They study mutating memes on Facebook

rank	copies	variant
n1	71831	somewhere right now a nurse is getting yelled at for being late with pain meds while holding her bladder because she doesn t have time to pee starving because she missed her break being pooped peed bled on and is missing her family while taking care of yours in the minute you took to read this nurses all over the world are saving lives re post this if you are a nurse love a nurse or appreciate one
n2	18068	somewhere right now a nurse is getting yelled at for being late with meds holding their bladder because they don t have time to pee starving because they missed lunch being peed on puked on pooped on bled on and is missing their family while taking care of yours in the minute it took you to read this nurses all over the world are saving lives repost if you are a nurse love a nurse or appreciate a nurse

(Adamic et al., 2016)

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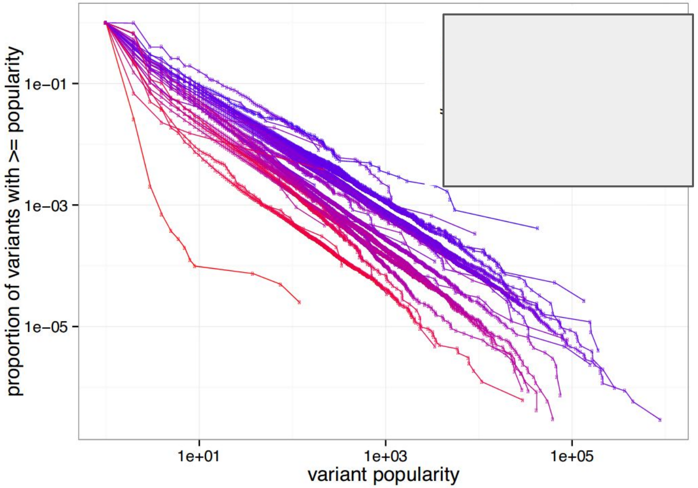

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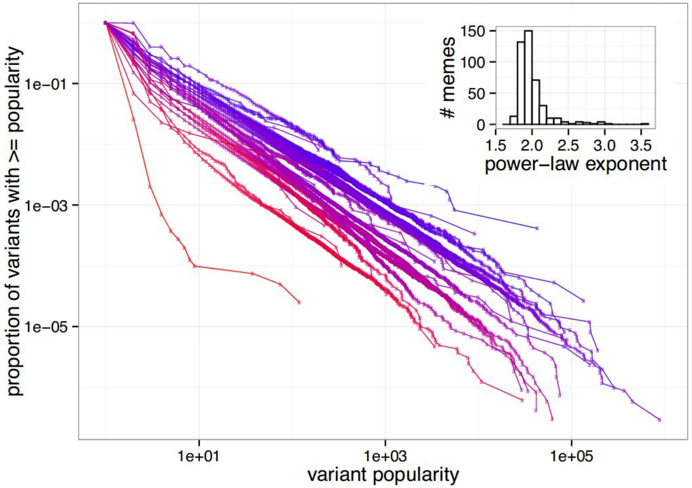

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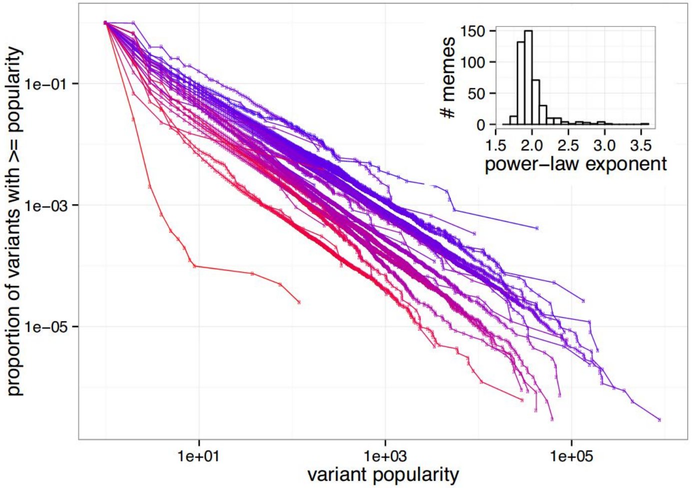

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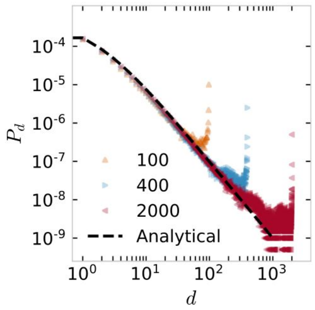

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Simulations match analytical solution

(Adamic et al., 2016)

Our study: (Juul & Strogatz, 2020)

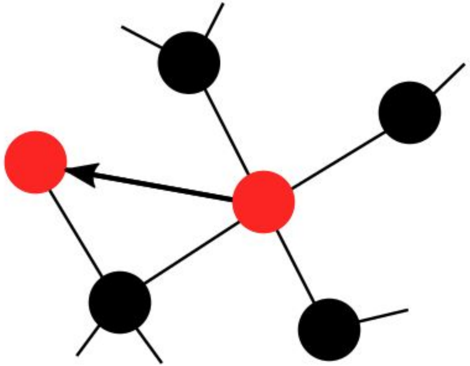
Online diffusion

Does false news spread farther, faster, deeper, and more broadly than the truth?

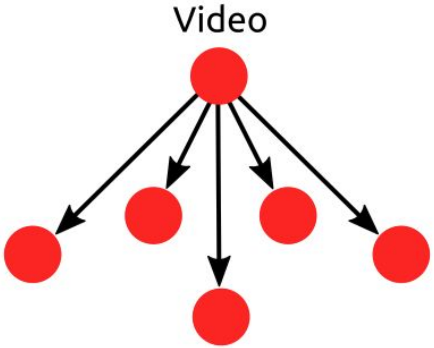
Our study in PNAS: (Juul & Ugander, 2021)

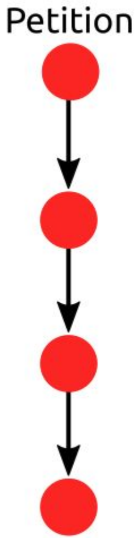
Online diffusion

How people study spreading:



Track spreading online





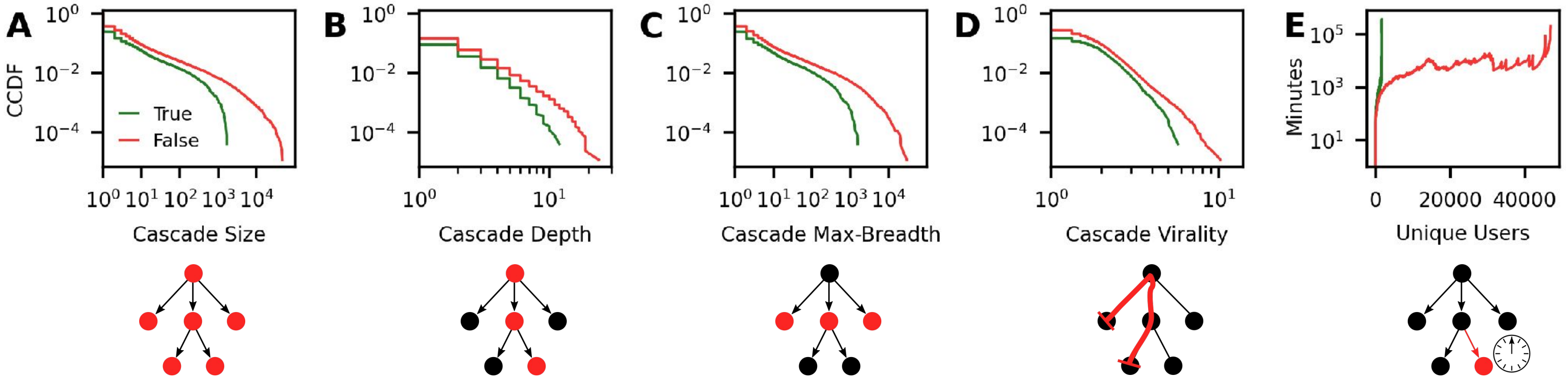
Compare “*cascades*”
(rooted, directed trees)

(Liben-Nowell and Kleinberg, 2008; Golub and Jackson, 2010; Goel et al, 2012; Goel et al., 2016; Vosoughi et al., 2018; Zhao et al., 2020)

True and false news on Twitter.

Vosoughi *et al.* studied all verified false or true news on Twitter. Reported:

False news spreads farther, faster, deeper and more broadly than the truth

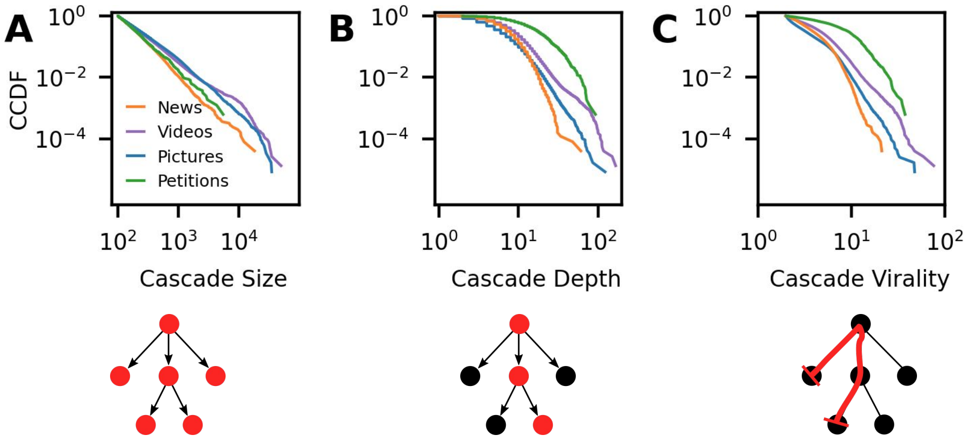


(Vosoughi et al., 2018)

Content types on Twitter.

Goel *et al.* studied news, videos, pictures and petitions spreading on Twitter:

Reported that petition cascades are deeper and more viral than other content.



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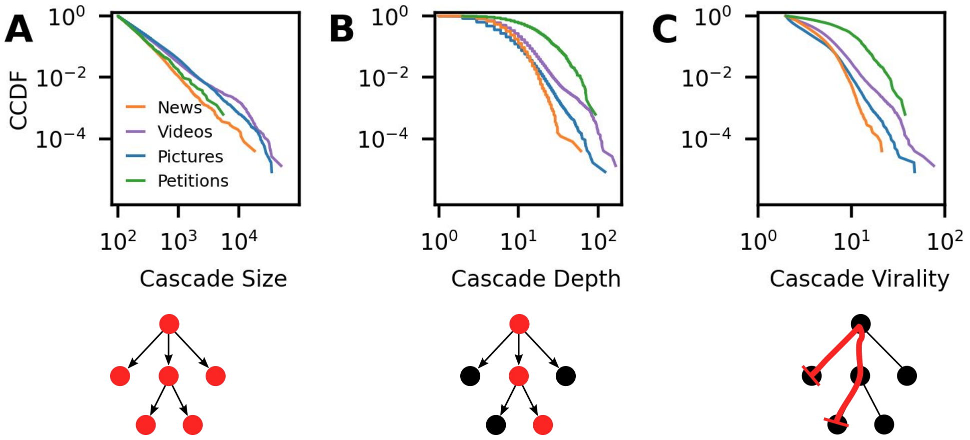


BUT...

(Goel et al., 2016)

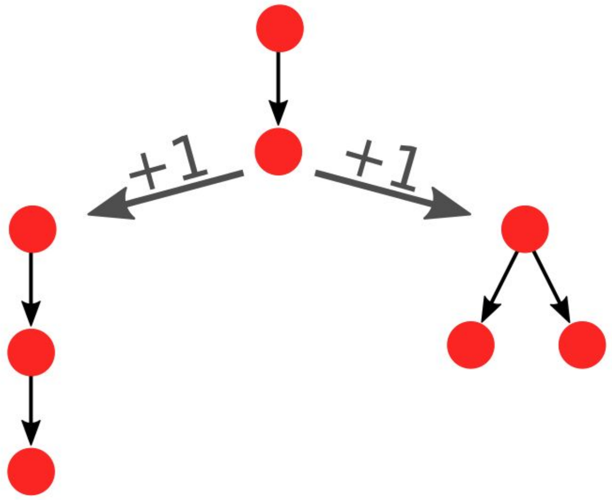
True and false news on Twitter.

Cascade features are <u>not independent</u>.

We expect larger cascades to be

- Broader
- Deeper
- Have higher mean pairwise distance
- (Faster?)

Q: Do size differences drive observations?
Test: Ensure identical sizes when comparing.



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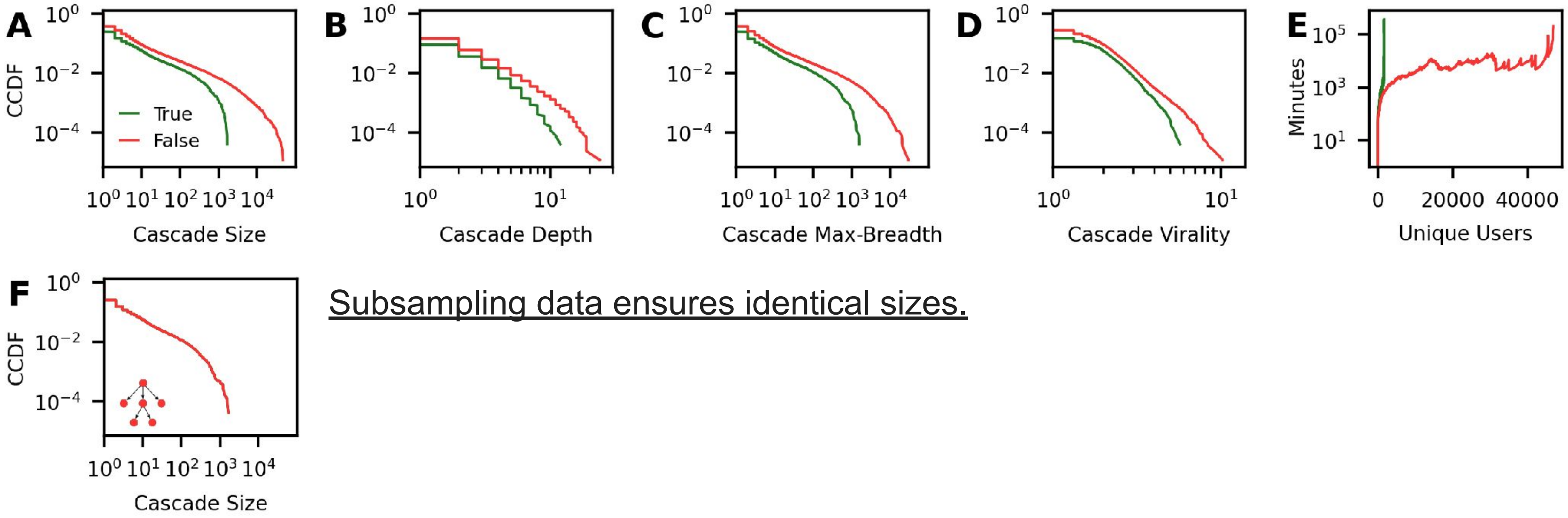

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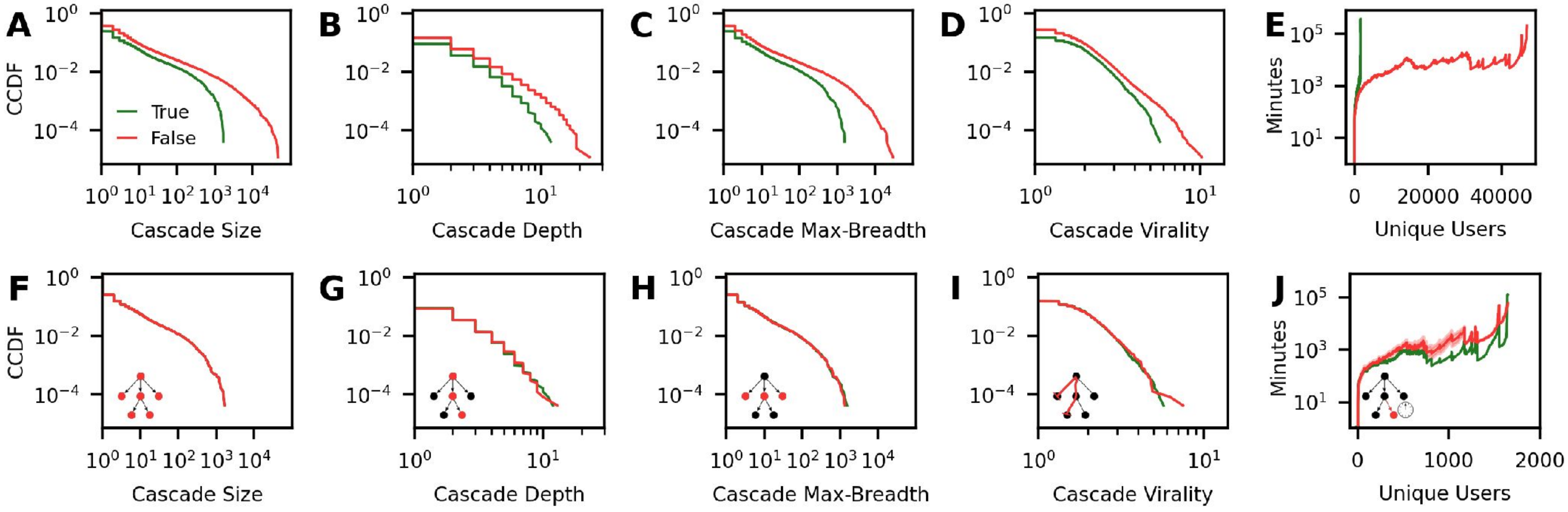

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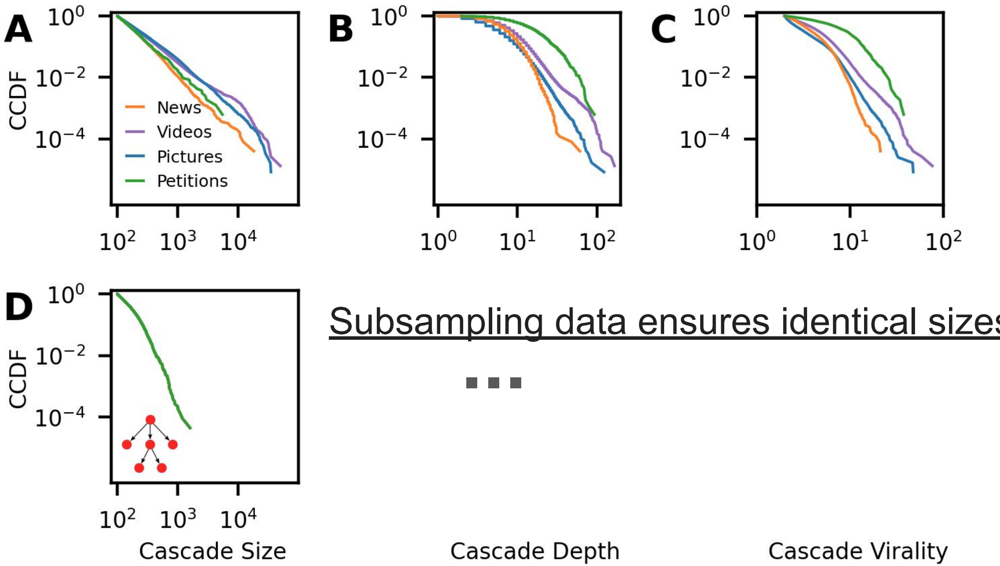
Reported that petition cascades are deeper and more viral than other content.



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...

(Goel et al., 2016)

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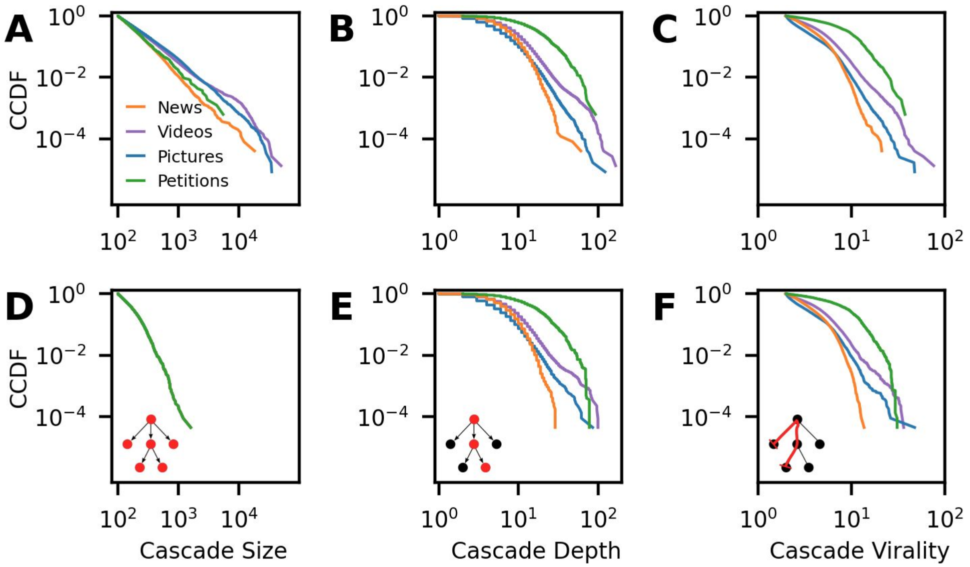


(Goel et al., 2016)

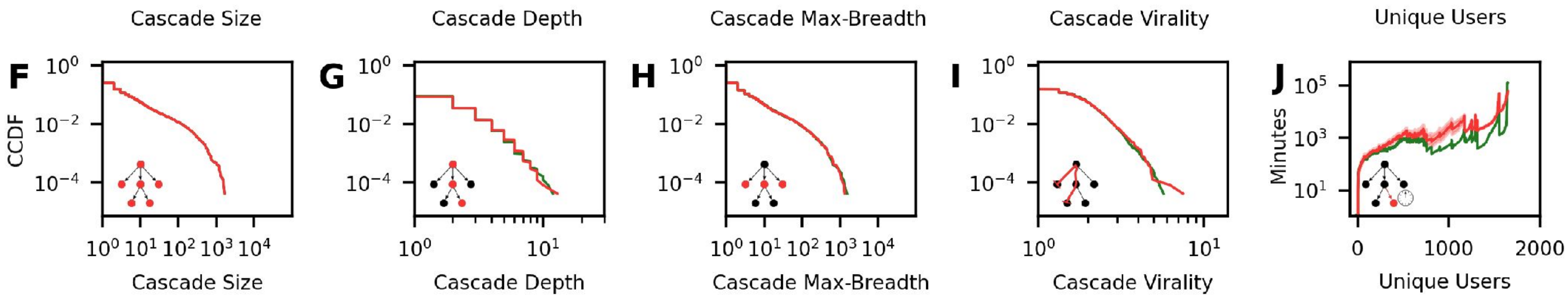
True and false news on Twitter.

Vosoughi et al. studied all verified false or true news on Twitter. Reported:

~~False news spread farther, faster, deeper and more broadly than the truth~~

False news gets bigger but **there is no significant difference** between false and true cascades of the same size.

Q: What does this tell us about the diffusion rules?

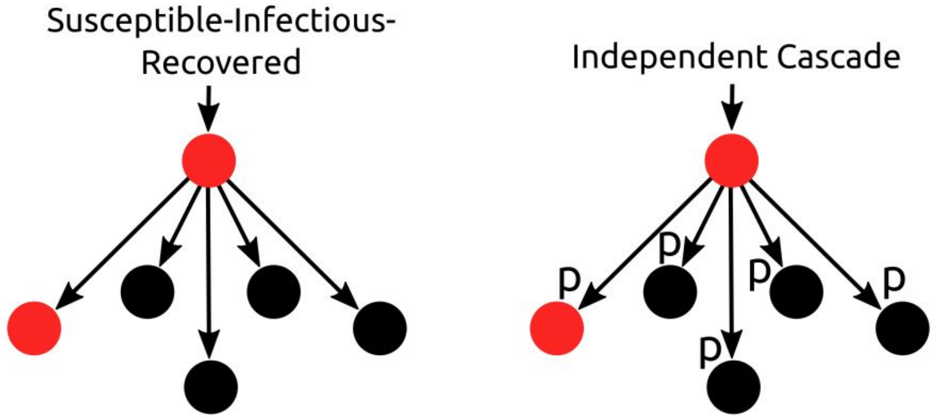


So what does this tell us?

Create cascades using 2 different models.

On infinite cliques both have just 1 parameter, R0 (the infectiousness).

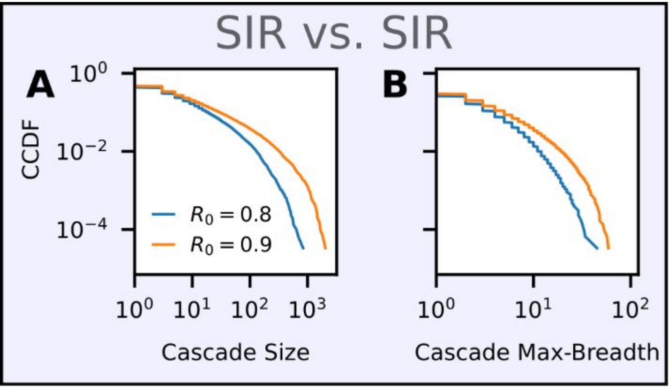
Q: What happens when comparing cascades created with different R0?



Model simulations (SIR and IC)

Each dataset: 30,000 simulated cascades.

Each model: 2 values of R0



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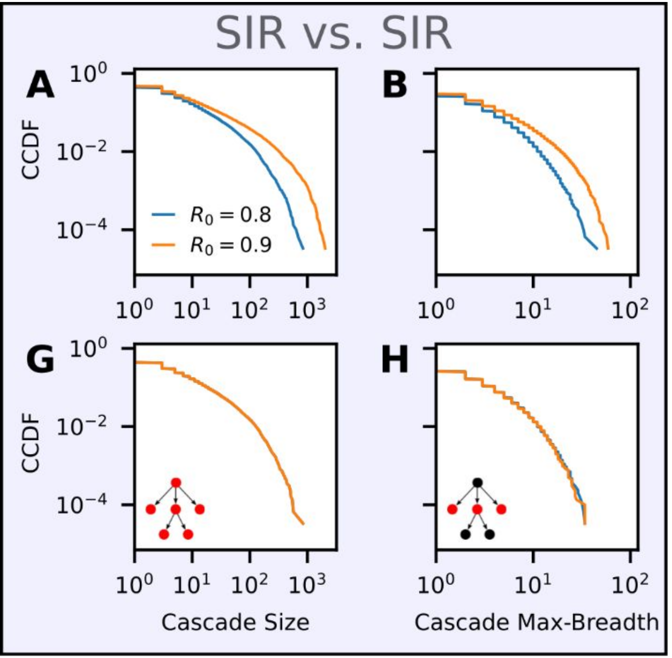

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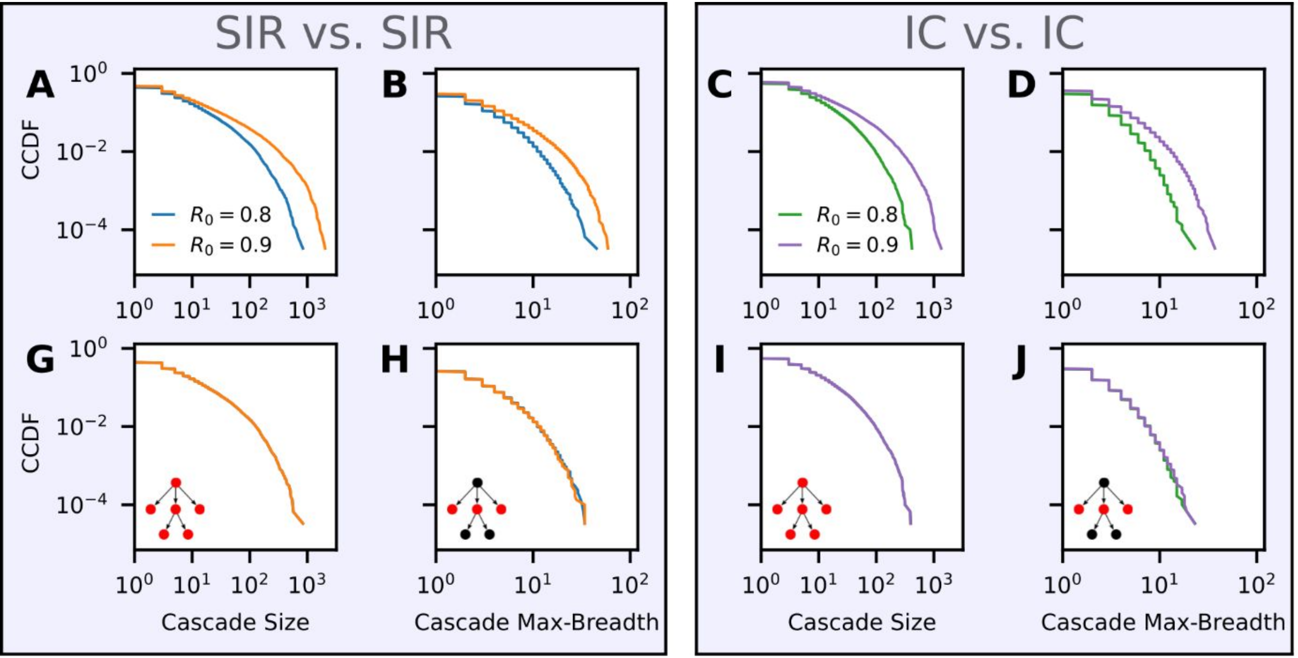

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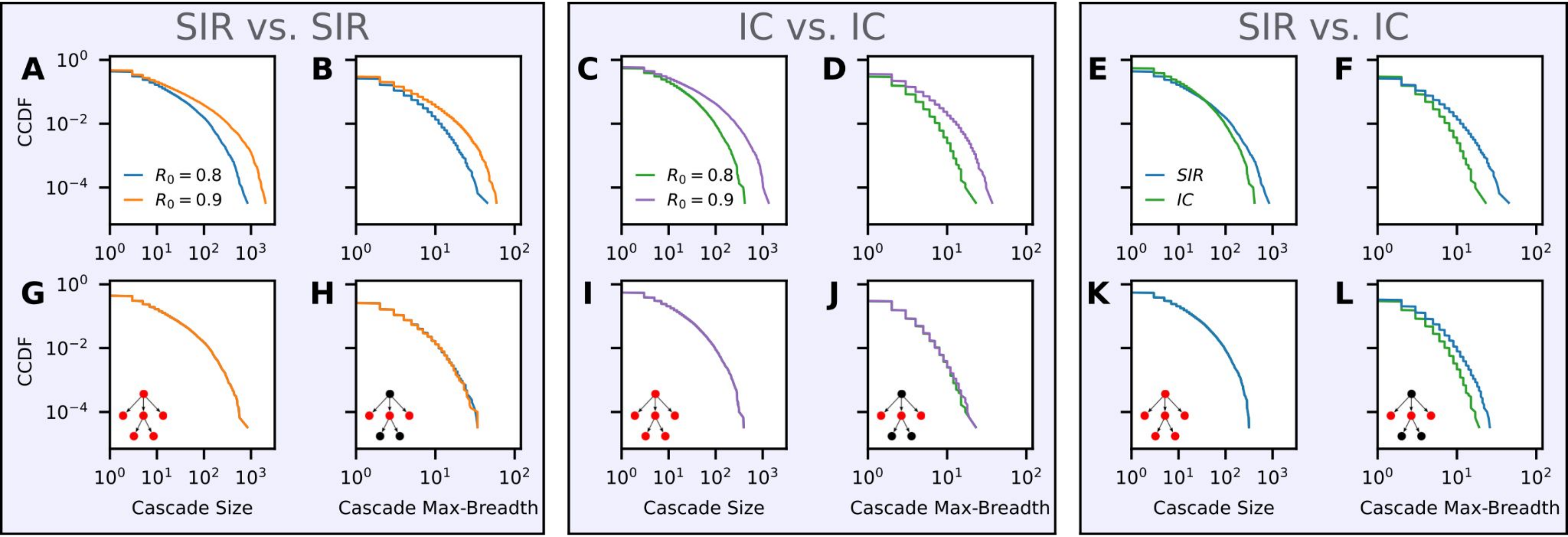

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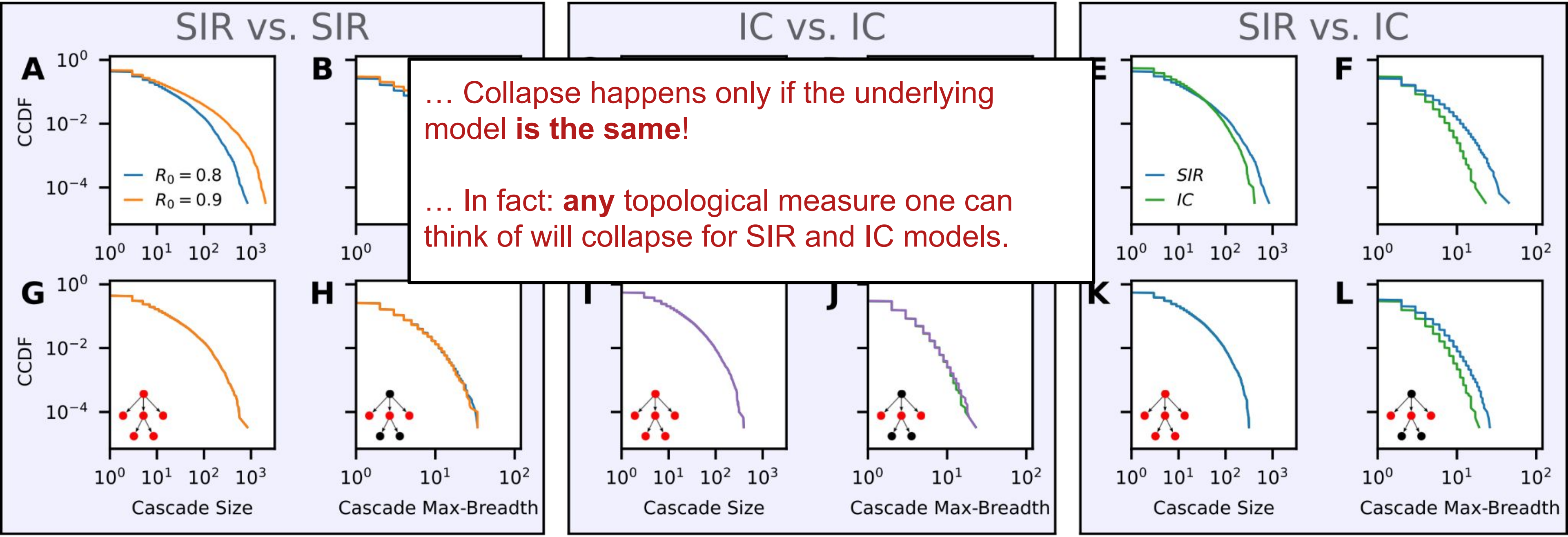

… Collapse happens only if the underlying model **is the same**!

… In fact: **any** topological measure one can think of will collapse for SIR and IC models.

Model simulations (SIR and IC)

Theorem 1. ***(SIR and IC model)*** *Let* $P_{\mathrm{SIR}}(T|s, R_0)$ *and* $P_{\mathrm{IC}}(T|s, R_0)$ *denote the probability of obtaining the tree* T *when growing a self-terminated cascade of size* s *on the infinite clique using the Susceptible-Infectious-Recovered (SIR) model with parameter* $R_0 = r_I / r_R$ *or the Independent-Cascade (IC) model with parameter* R_0*, respectively. Then both* $P_{\mathrm{SIR}}(T|s, R_0)$ *and* $P_{\mathrm{IC}}(T|s, R_0)$ *are independent of* R_0*.*

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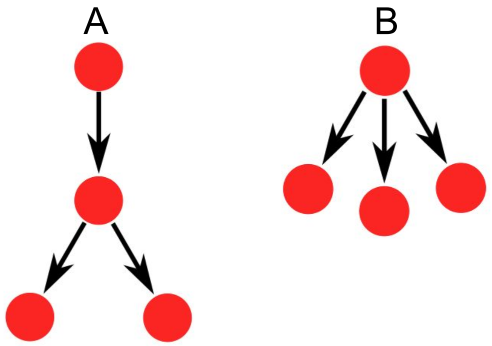


In words: A higher R_0 makes larger cascades more likely. But if we look only at cascades of a specific size *s*, any SIR simulation will create any cascade, C, with identical probability. Same for IC model.

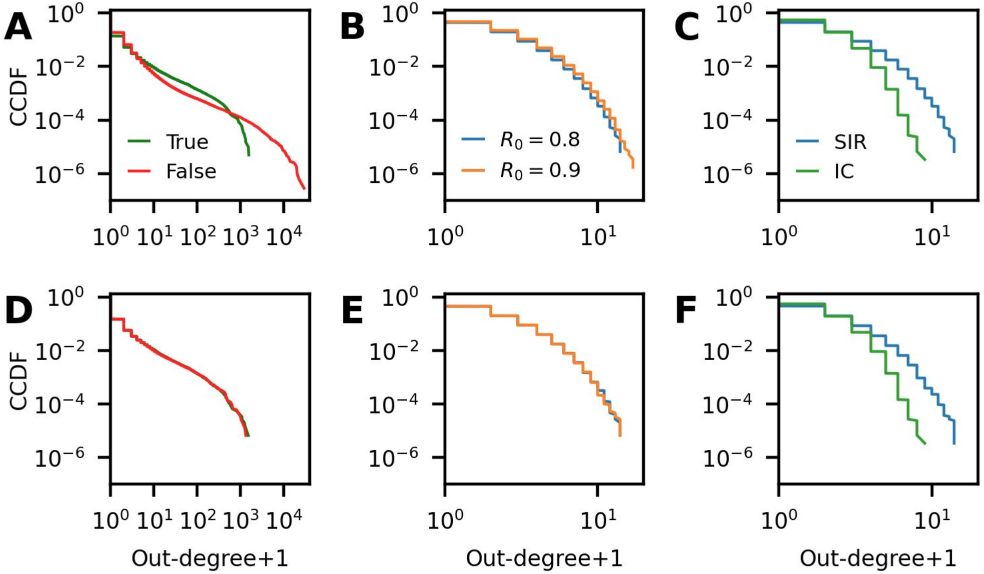
Intuition:
To create A and B with SIR, you need exactly
- 3 infection events,
- 4 removal events.

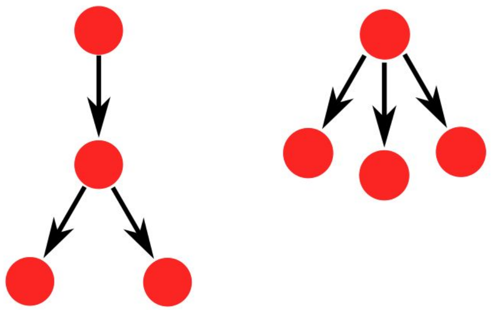
The ordering of these events / *who is chosen to infect and get removed* determines whether A or B is created. R_0 influences the likelihood of these events, but not the ordering.

Model simulations (SIR and IC)

Is this what is going on for false/true news data?

If distributions over trees are identical, so are degree distributions





Our study: (Juul & Ugander, 2021)

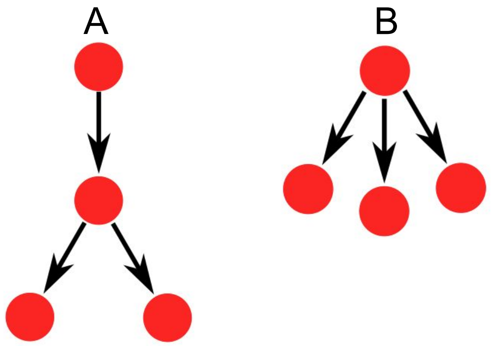
Growing cascades

What can we tell about contagion while it is still spreading?

Our study is currently in preparation: (Juul & Ugander, ?)

Growing cascades

Theorem 1. ***(SIR and IC model)*** *Let $P_{\mathrm{SIR}}(T|s, R_0)$ and $P_{\mathrm{IC}}(T|s, R_0)$ denote the probability of obtaining the tree T when growing a self-terminated cascade of size s on the infinite clique using the Susceptible-Infectious-Recovered (SIR) model with parameter $R_0 = r_I/r_R$ or the Independent-Cascade (IC) model with parameter R_0, respectively. Then both $P_{\mathrm{SIR}}(T|s, R_0)$ and $P_{\mathrm{IC}}(T|s, R_0)$ are independent of R_0.*



It would be great to understanding contagion before it stops spreading!

Growing cascades

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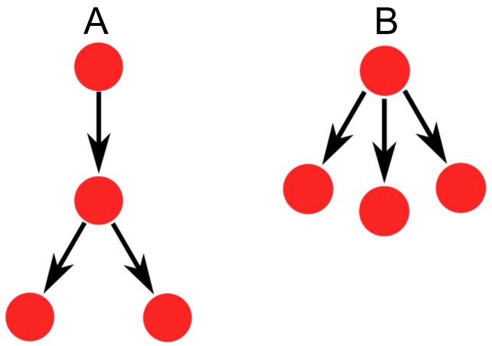

It would be great to understanding contagion before it stops spreading!

Q: If we observe A and B, and they are still growing, can we tell if they are results of different contagion processes?

(Slides with preliminary results excluded)

Conclusions

Cascade structure can indicate infectiousness, mutant impact.

Even without an advantage in infectiousness, the impact of a mutant strain is expected to be very large.

Although false news does spread farther, faster, deeper and more broadly than the truth, these differences seem to be driven by size-differences.

Not so for differences between cascades of petitions, videos, pictures, news.

2 different analyses indicate that attempts to limit spread of false news should focus on limiting the mean "infectiousness" of the false news.

Other ongoing studies:

- Using cascade structure to understand the importance of superspreaders (see (Goel et al., 2016))
- Cascade structure of the COVID-19 epidemic in Denmark

References (my work):

Juul, J. S., & Strogatz, S. H. (2020). Descendant distributions for the impact of mutant contagion on networks. Physical Review Research, 2(3), 033005.

Juul, J. L., & Ugander, J. (2021). Comparing information diffusion mechanisms by matching on cascade size. Proceedings of the National Academy of Sciences, 118(46), e2100786118.

Juul, J. L., & Ugander, J. In preparation

For more on cascades, see:

Juul, J. S., & Porter, M. A. (2019). Hipsters on networks: How a minority group of individuals can lead to an antiestablishment majority. Physical Review E, 99(2), 022313.

...Thanks!

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