LECTURE 9:CONTAGION AND VIRAL MARKET

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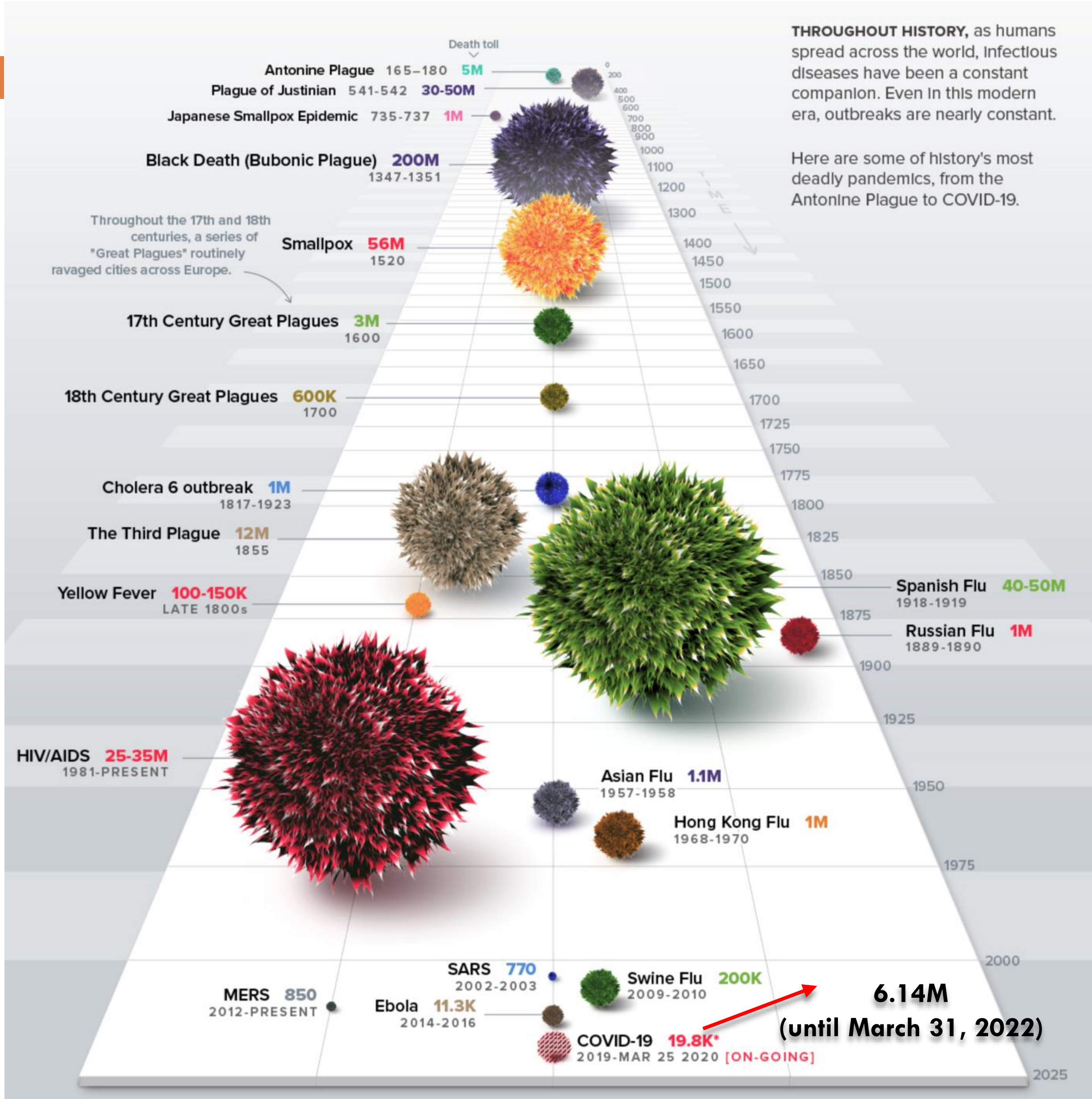
CSIT 6000K: Social Networks and Social Computing: A Data Science Perspective

Thursdays 07:30 PM - 10:20 PM

History of Pandemics



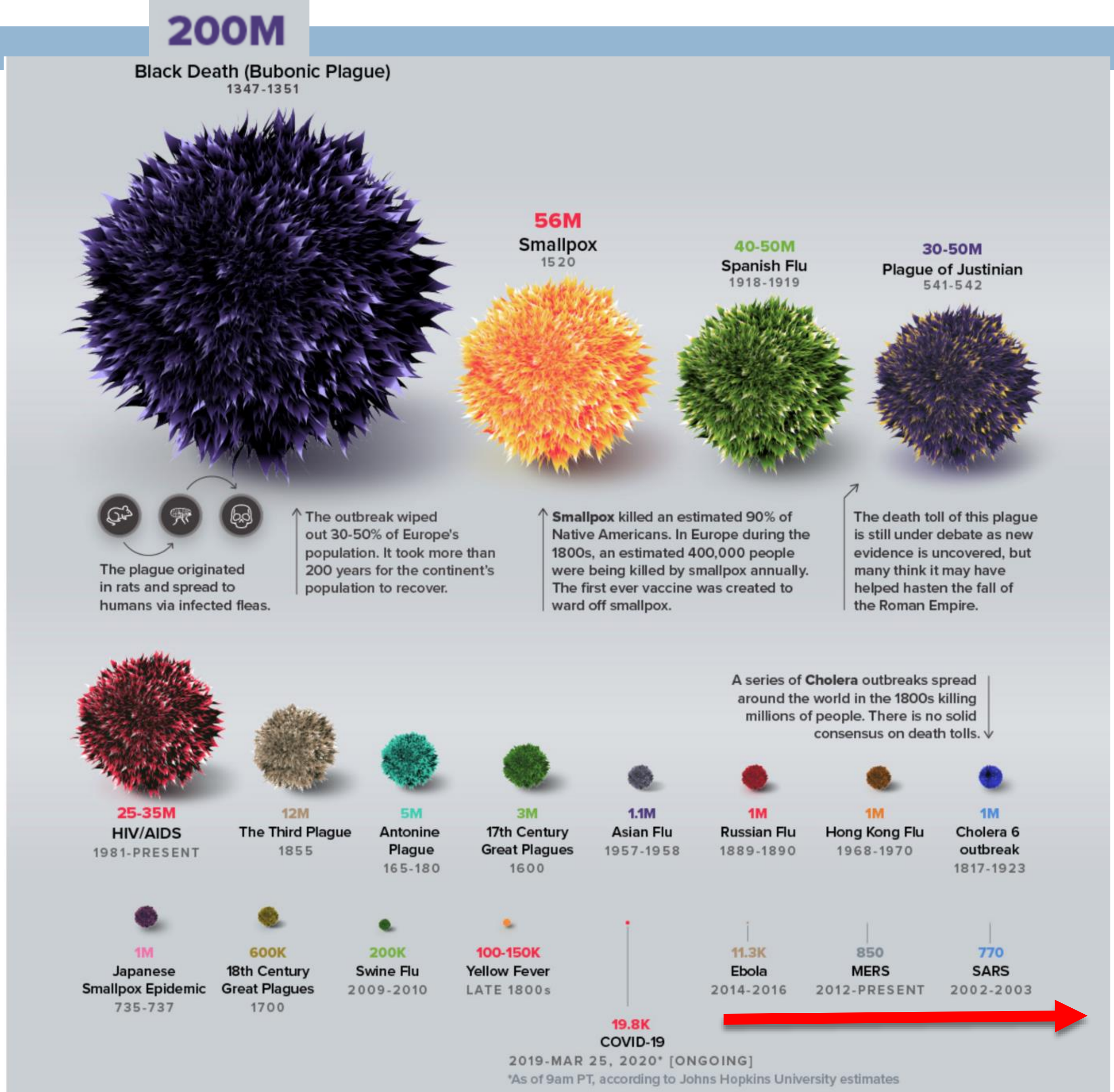
PAN.DEM.IC (of a disease) prevalent over a whole country or the world.

Number of infected People by Covid-19:
487M
(Until March 31, 2022)

WHO officially declared COVID-19 a pandemic on March 111, 2020.

https://www.visualcapitalist.com/history-of-pandemics-deadliest/

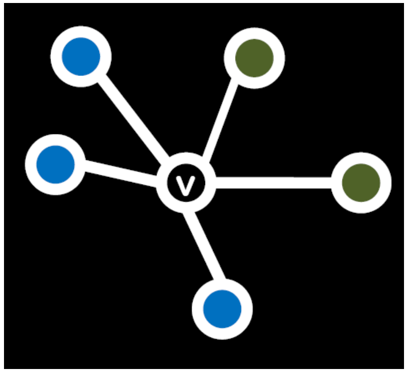
Death Toll of Pandemics



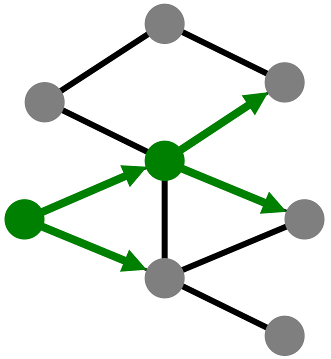
6.14M
(until March 31, 2022)

Models of Cascading Behavior

- Last time:
  Decision Based Models
  - Utility based
  - Deterministic
  - "Node" centric: A node observes decisions of its neighbors and makes its own decision
  - Require us to know too much about the data



- **Today: Probabilistic Models**
  - Let's you do things by observing data
  - We loose "why people do things"

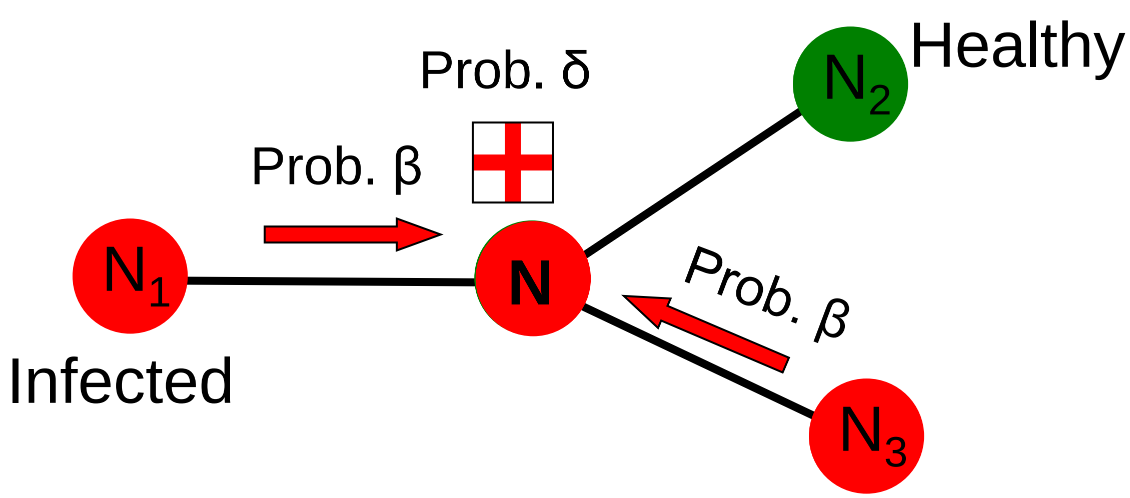


CLASSICAL MODELS OF DISEASE SPREADING

Spreading Models of Viruses

Virus Propagation: 2 Parameters:

- **(Virus) birth rate β:**
  - probability than an infected neighbor attacks
- **(Virus) death rate δ:**
  - probability that an infected node heals



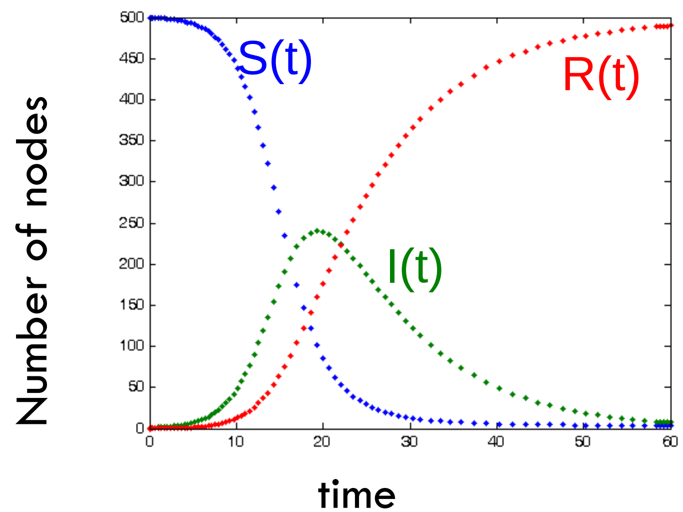
SIR Model

- **SIR model:** Node goes through phases

  - Models chickenpox or plague:
    - Once you heal, you can never get infected again
- **Assuming perfect mixing (anyone may infect anyone) the model dynamics is:**

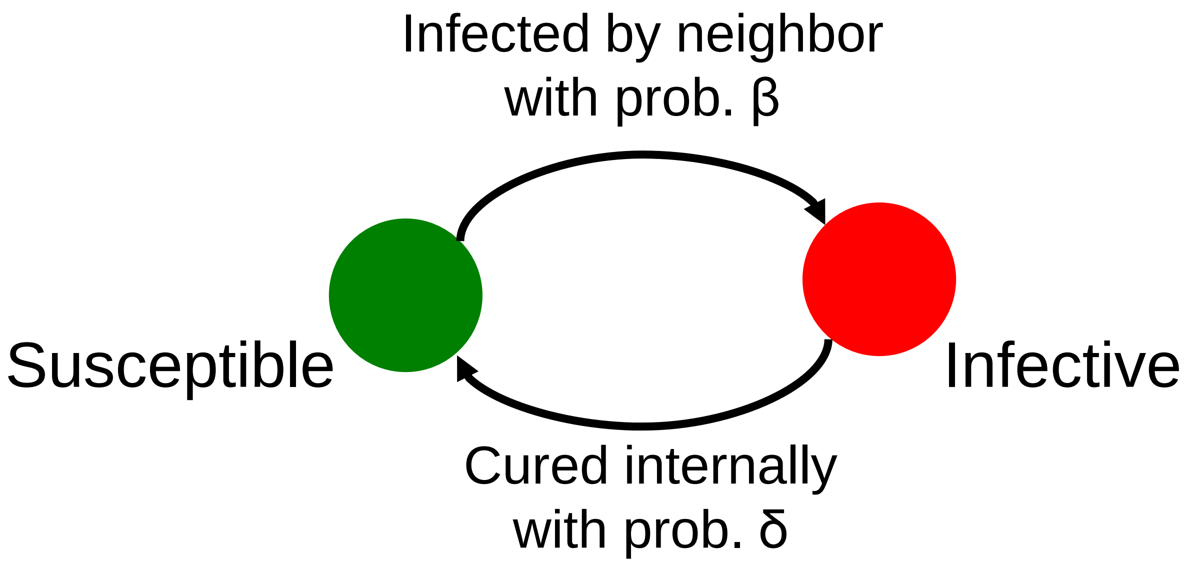
$$\frac{dS}{dt} = -bSI \qquad \frac{dR}{dt} = dI$$

$$\frac{dI}{dt} = bSI - dI$$

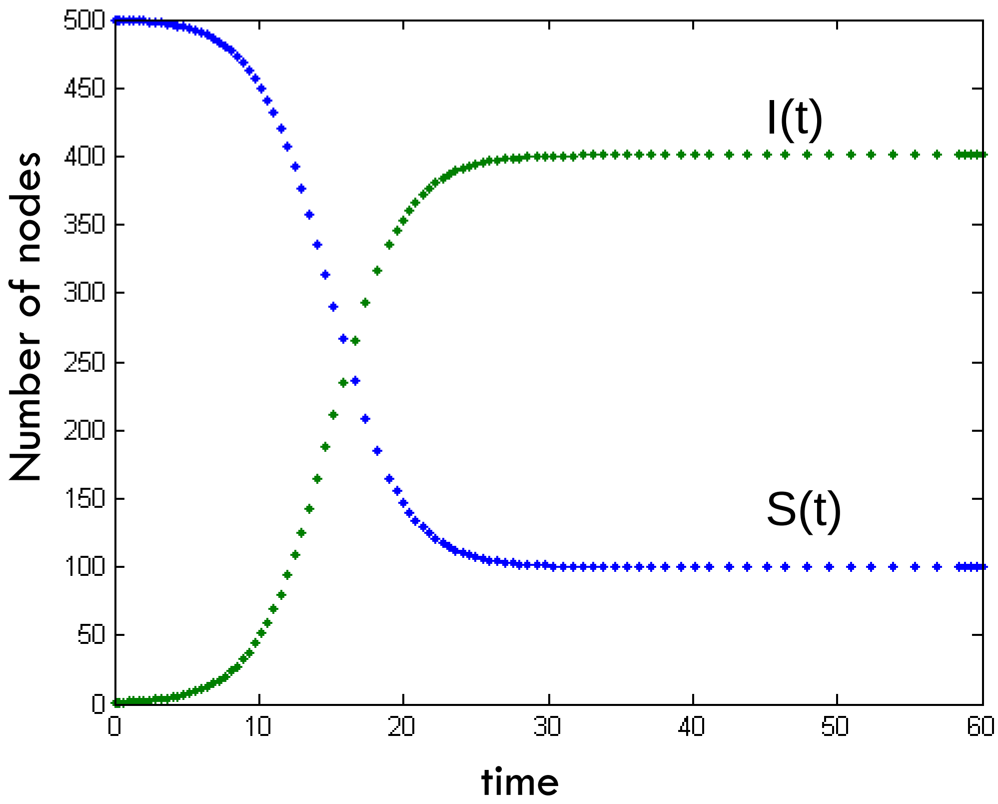


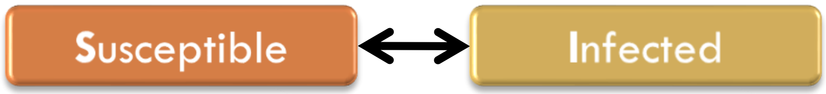
SIS Model

- **Susceptible-Infective-Susceptible (SIS) model**
- Cured nodes immediately become susceptible
- **Virus "strength": $s = \beta / \delta$**
- **Node state transition diagram:**



SIS Model





- **Models flu:**
  - Susceptible node becomes infected
  - The node then heals and become susceptible again
- **Assuming perfect mixing (anyone may infect anyone):**

$$\frac{dS}{dt} = -\beta SI + \delta I$$

$$\frac{dI}{dt} = \beta SI - \delta I$$

Question: Epidemic threshold *t*

- **SIS Model:**
  Epidemic threshold of an arbitrary graph G is τ, such that:
  - If virus strength $s = \beta / \delta < \tau$
    the epidemic can not happen
    (it eventually dies out)

- **Given a graph what is its epidemic threshold?**

Epidemic Threshold in SIS Model

- **We have no epidemic if:**

Epidemic threshold

(Virus) Death rate

$$\boxed{\beta/\delta < \tau = 1/\lambda_{1,A}}$$

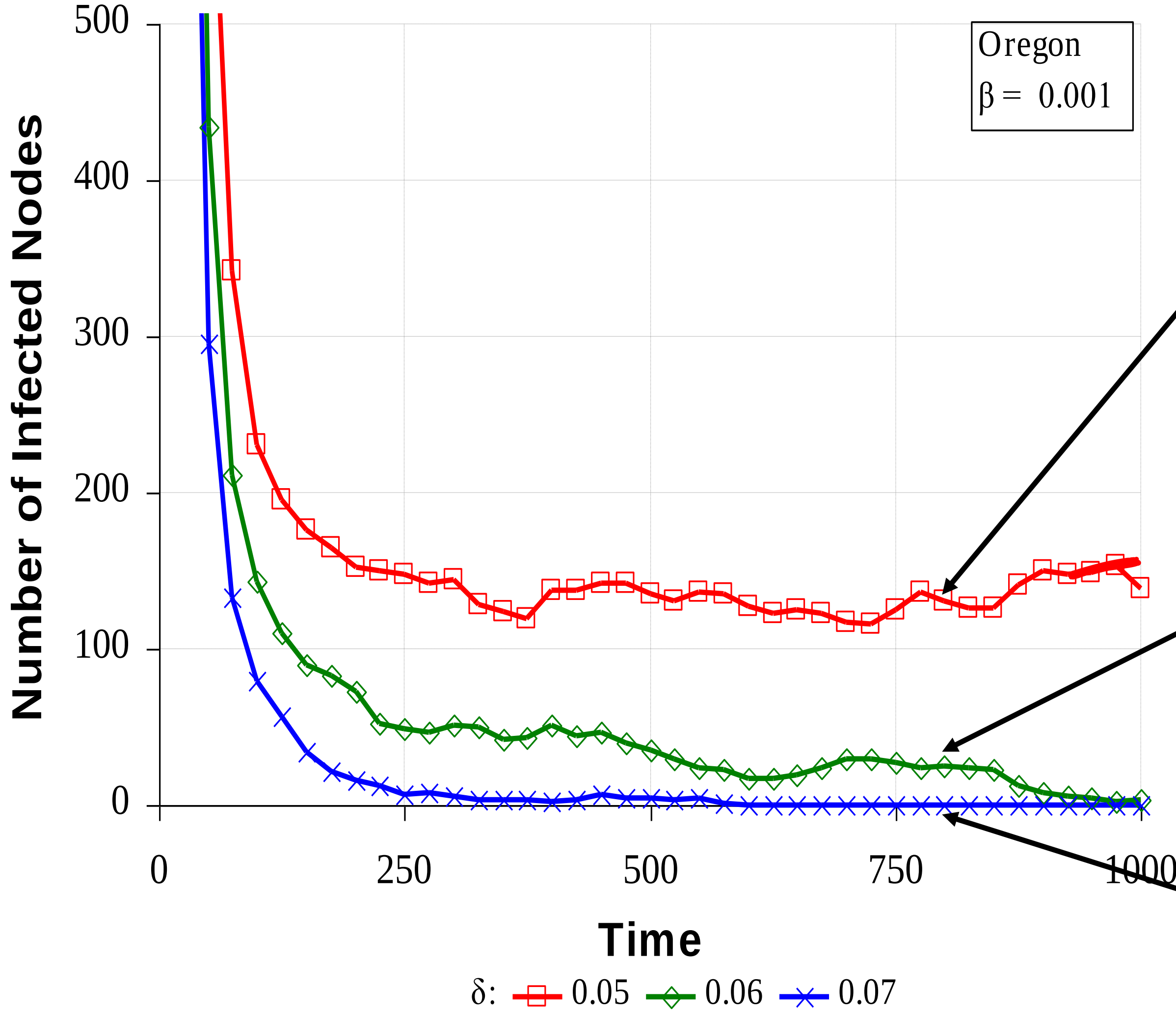
(Virus) Birth rate

largest eigenvalue of adj. matrix ***A***

► ***$\lambda_{1,A}$ alone captures the property of the graph!***

Experiments (AS graph)

10,900 nodes and 31,180 edges



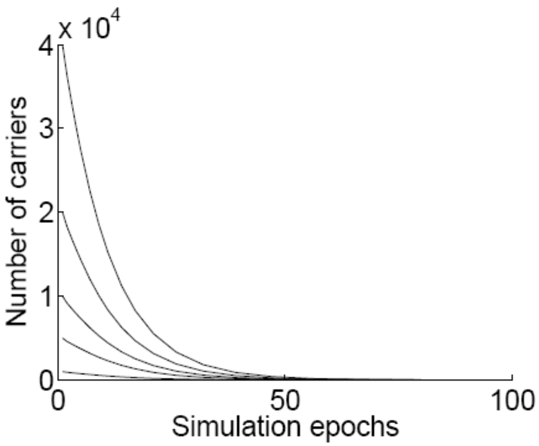
$\beta/\delta > \tau$ (above threshold)

$\beta/\delta = \tau$ (at the threshold)

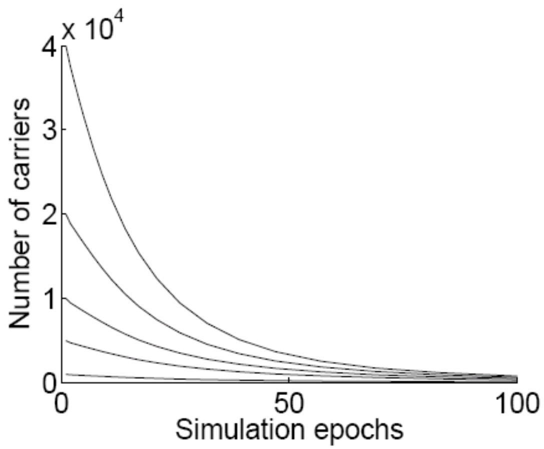
$\beta/\delta < \tau$ (below threshold)

Experiments

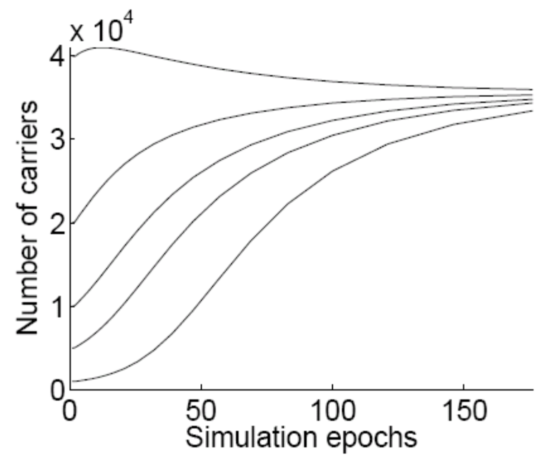
- Does it matter how many people are initially infected?



(a) Below the threshold, s=0.912



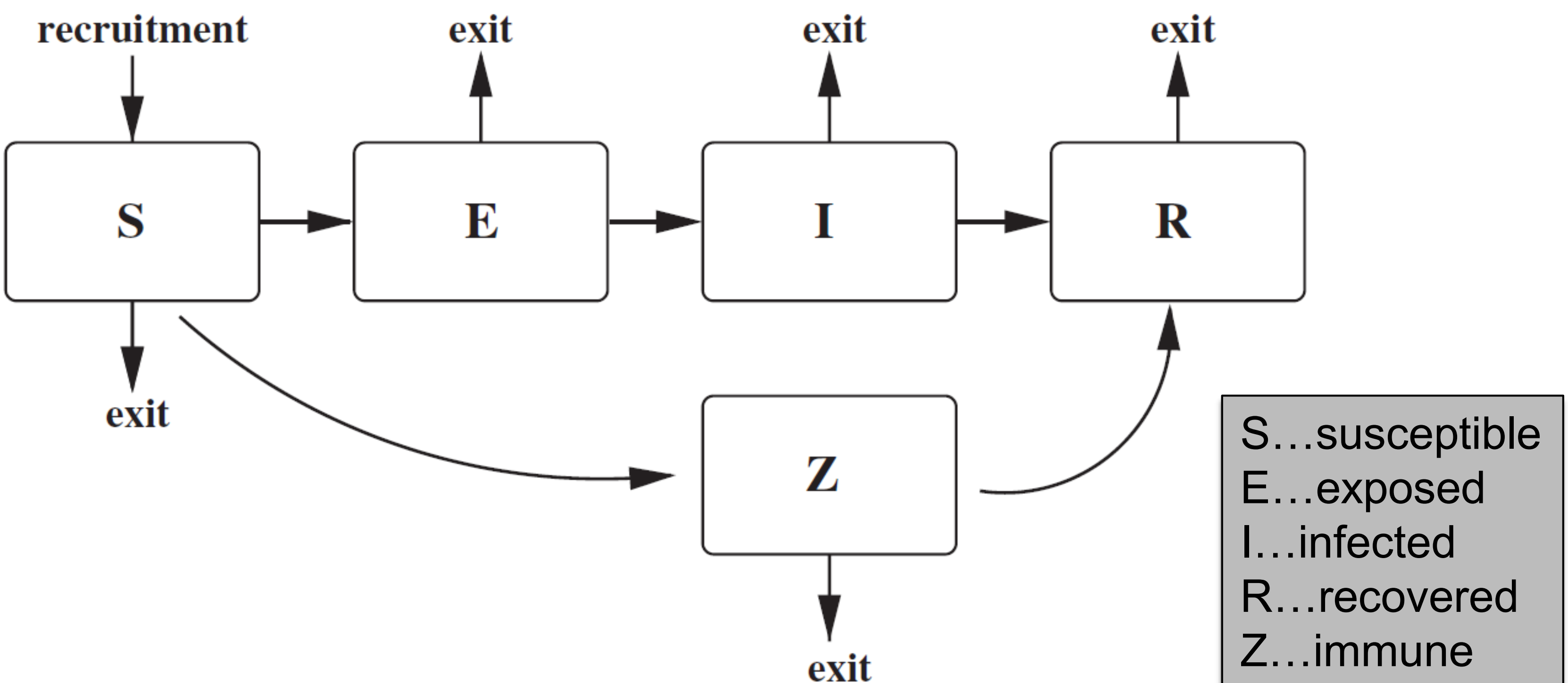
(b) At the threshold, s=1.003



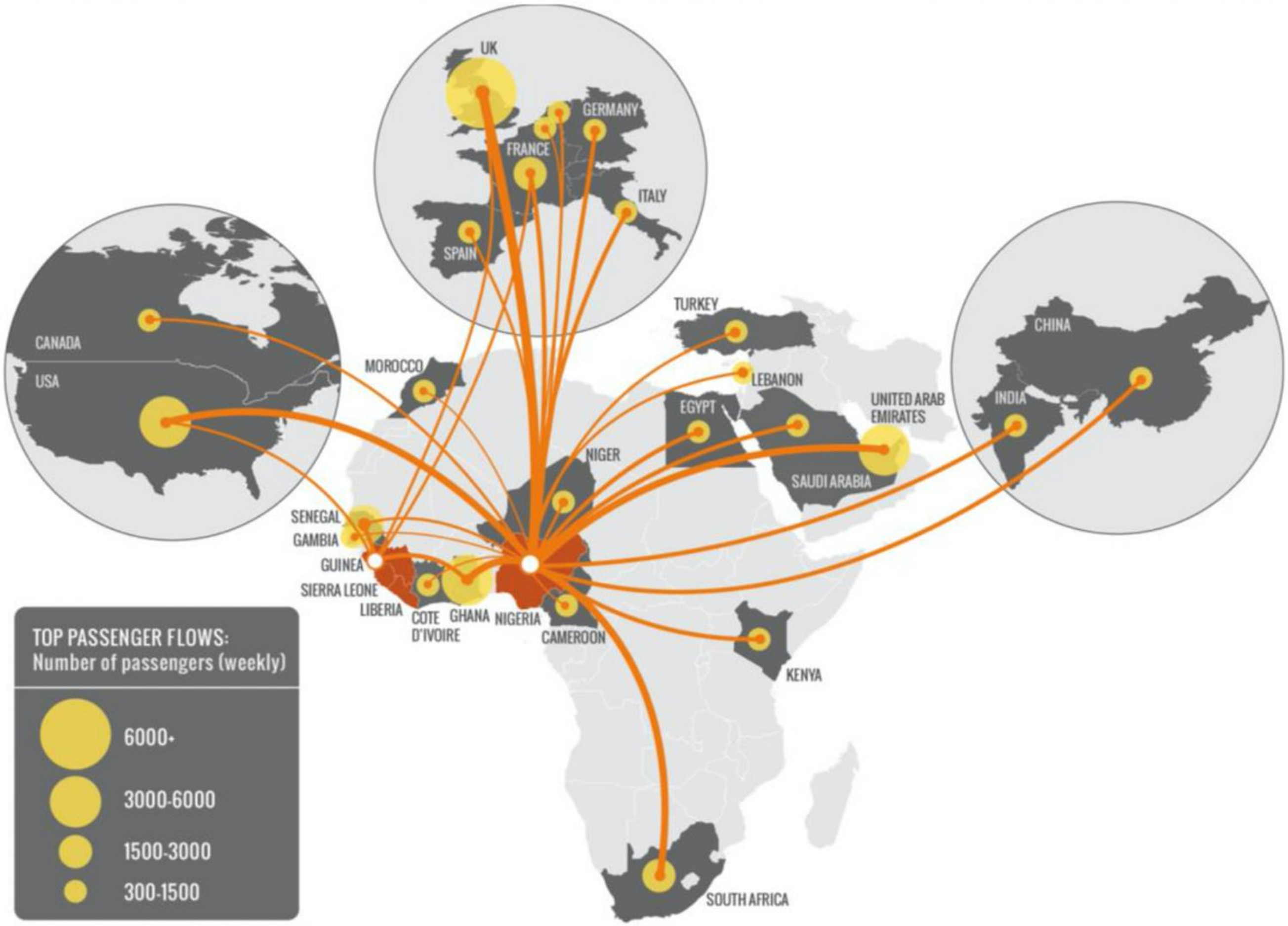
(c) Above the threshold, s=1.1

More Generally: S+E+I+R Models

- General scheme for epidemic models:
  - **Each node can go through phases:**
    - Transition probs. are governed by the model parameters

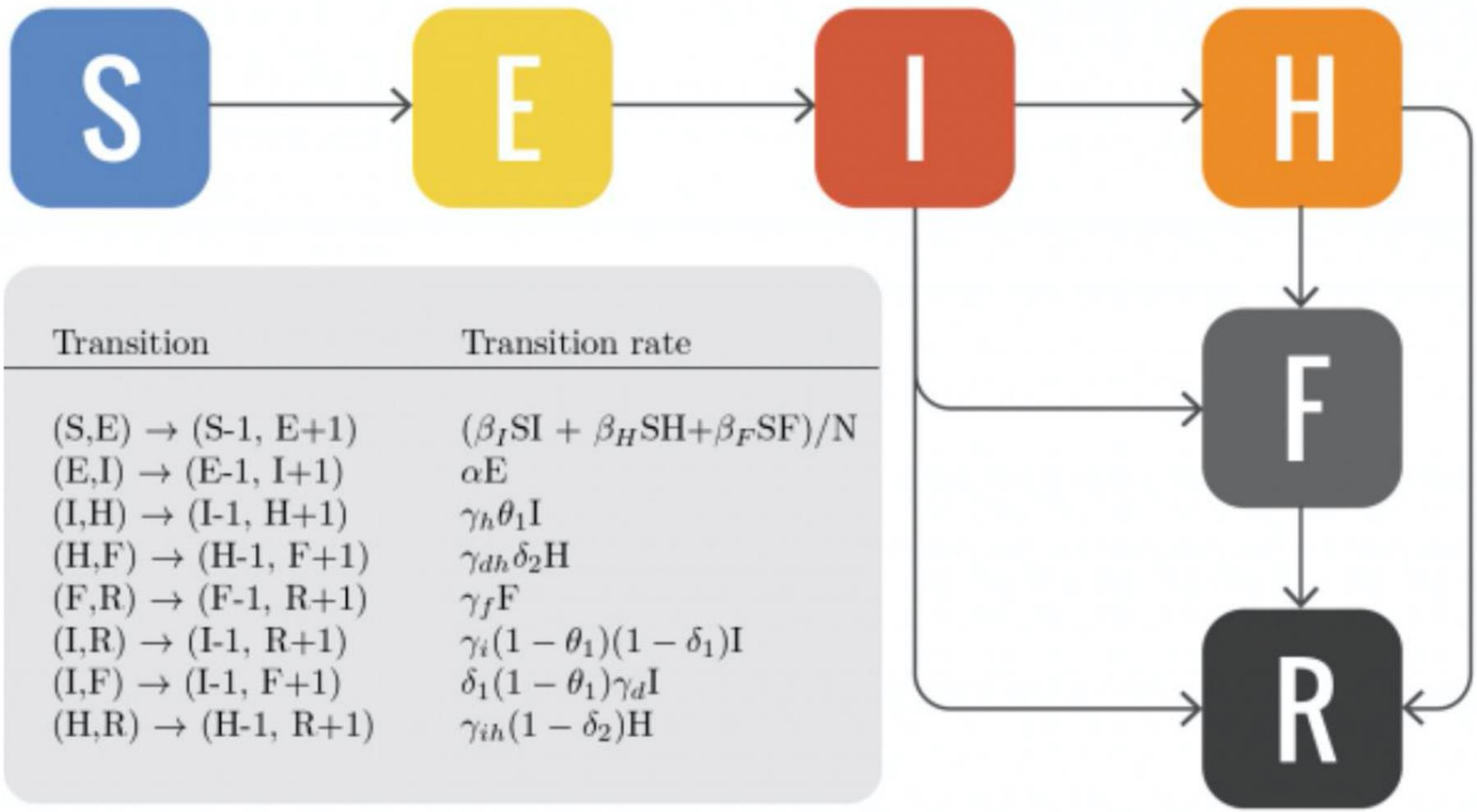


Modeling Ebola



[Gomes et al., Assessing the International Spreading Risk Associated with the 2014 West African Ebola Outbreak, PLOS Current Outbreaks, '14]

Example: Ebola



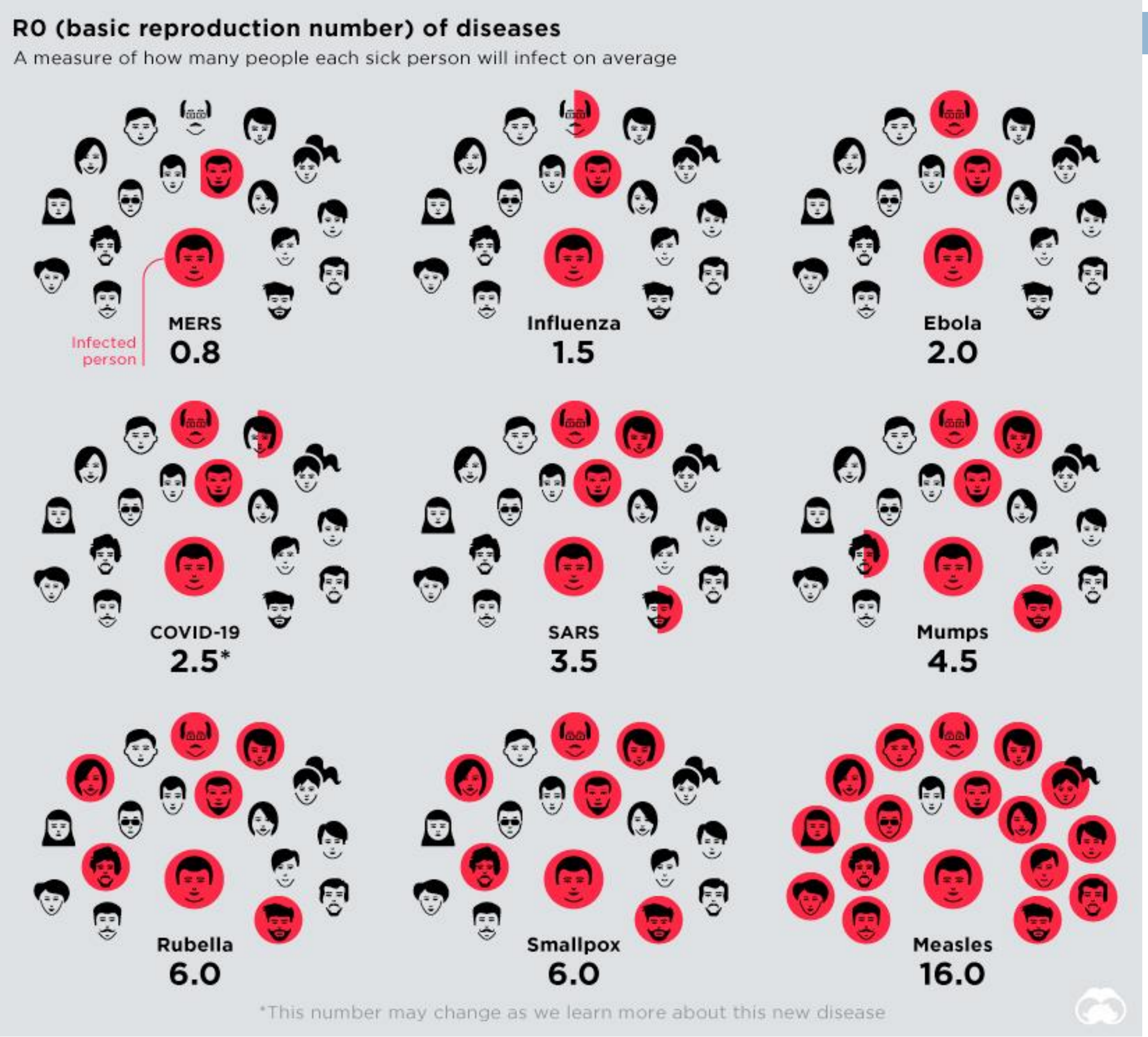
Transition	Transition rate
$(S,E) \to (S-1, E+1)$	$(\beta_I SI + \beta_H SH + \beta_F SF)/N$
$(E,I) \to (E-1, I+1)$	αE
$(I,H) \to (I-1, H+1)$	$\gamma_h \theta_1 I$
$(H,F) \to (H-1, F+1)$	$\gamma_{dh} \delta_2 H$
$(F,R) \to (F-1, R+1)$	$\gamma_f F$
$(I,R) \to (I-1, R+1)$	$\gamma_i (1-\theta_1)(1-\delta_1) I$
$(I,F) \to (I-1, F+1)$	$\delta_1 (1-\theta_1) \gamma_d I$
$(H,R) \to (H-1, R+1)$	$\gamma_{ih} (1-\delta_2) H$

S: susceptible individuals, **E:** exposed individuals, **I:** infectious cases in the community,
H: hospitalized cases, **F:** dead but not yet buried, **R:** individuals no longer transmitting the disease

[Gomes et al., Assessing the International Spreading Risk Associated with the 2014 West African Ebola Outbreak, *PLOS Current Outbreaks*, '14]

Disease Reproduction Number

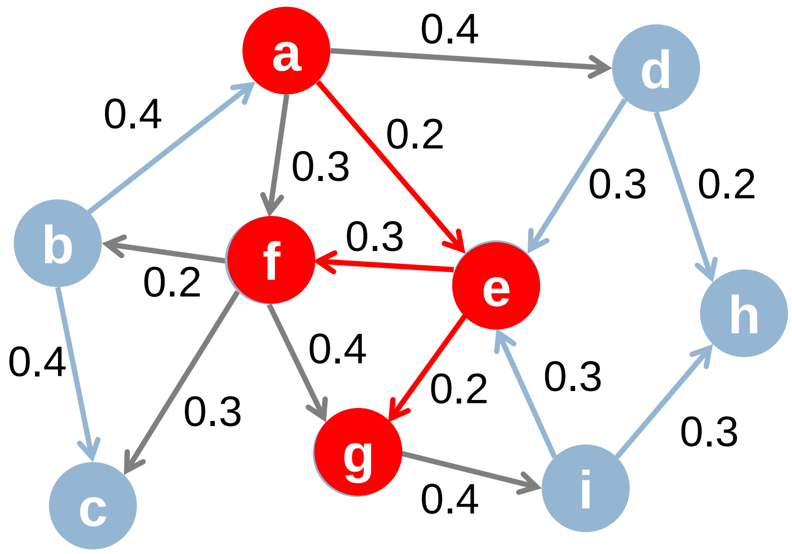
Covid Strain	R0
Alpha	2.79
Delta	5.08
Omicron	16



MODELS OF INFORMATION SPREAD

Independent Cascade Model

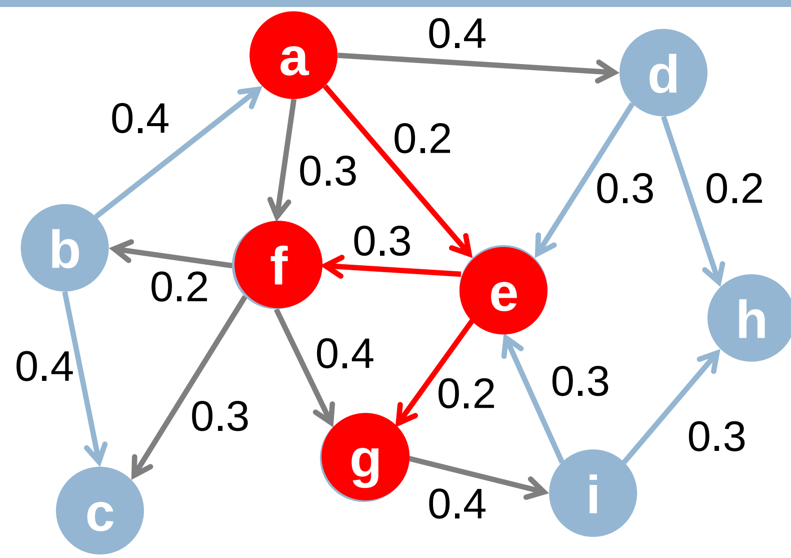
- **Initially some nodes *S* are active**
- Each edge (*u*,*v*) has probability (weight) p_{uv}



- **When node v becomes active:**
  - It activates each out-neighbor *v* with prob. p_{uv}
- **Activations spread through the network**

Independent Cascade Modal

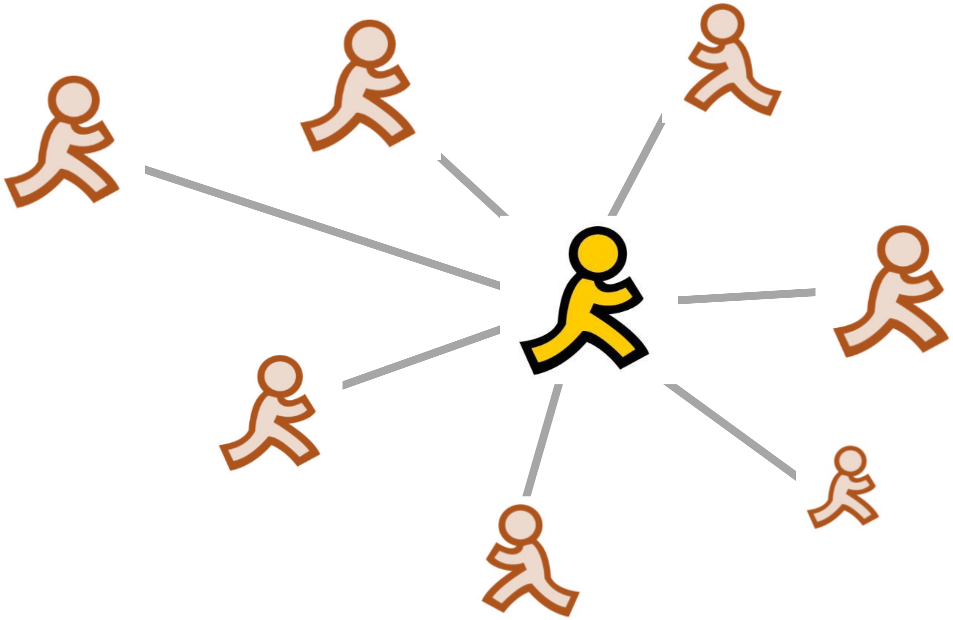
- **Independent cascade model is simple but requires many parameters!**
  - Estimating them from data is very hard [Goyal et al. 2010]



- **Solution:** Make all edges have the same weight (which brings us back to the SIR model)
  - Simple, but too simple
- **Can we do something better?**

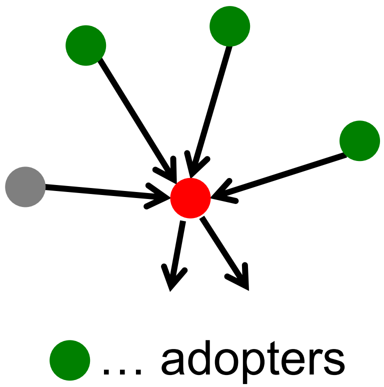
Exposures and Adoptions

- **From exposures** to **adoptions**
  - **Exposure**: Node's neighbor exposes the node to the contagion
  - **Adoption**: The node acts on the contagion

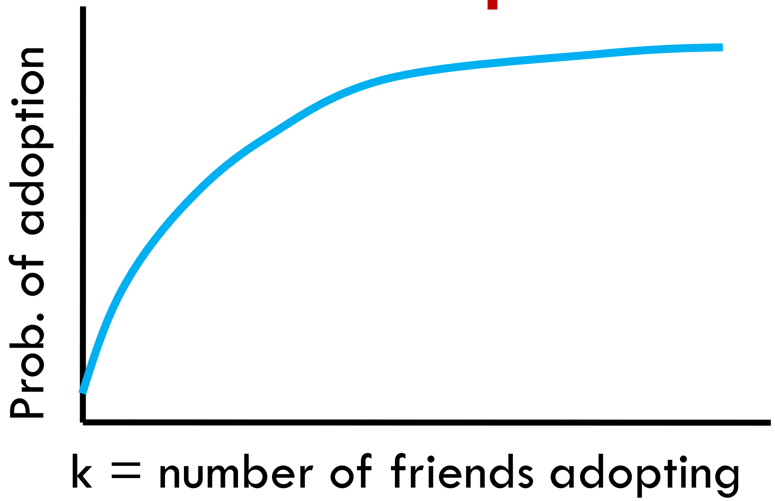


Exposure Curves

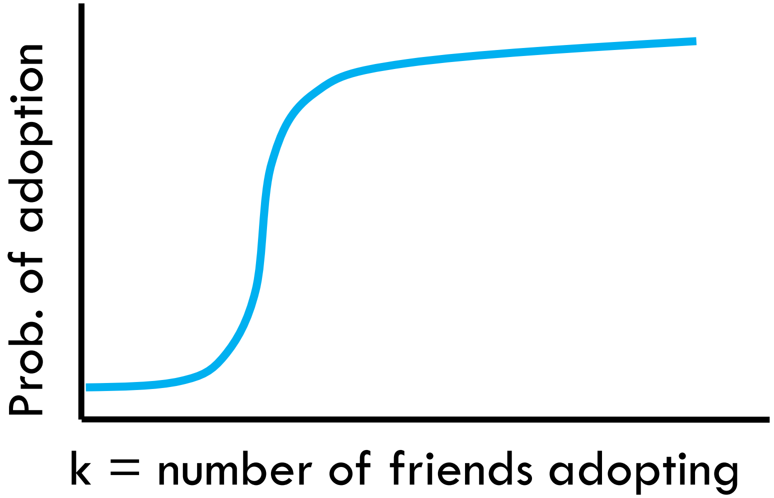
- **Exposure curve:**
  - Probability of adopting new **behavior** depends on the number of friends who have already adopted



- **What's the dependence?**



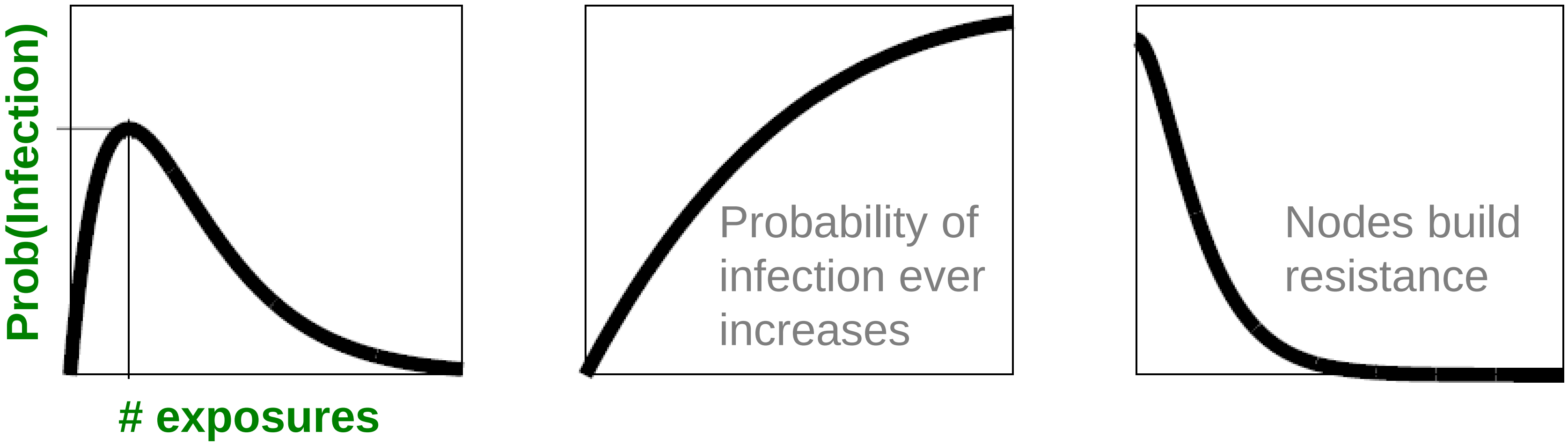
Diminishing returns:
Viruses, Information



Critical mass:
Decision making

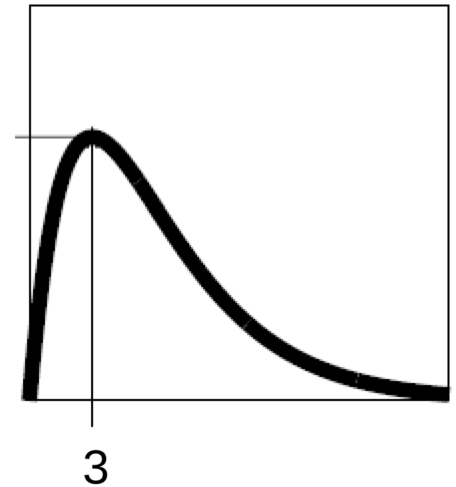
Exposure Curves

- **From exposures** to **adoptions**
  - **Exposure**: Node's neighbor exposes the node to information
  - **Adoption**: The node acts on the information
- **Adoption curve:**



Example Application

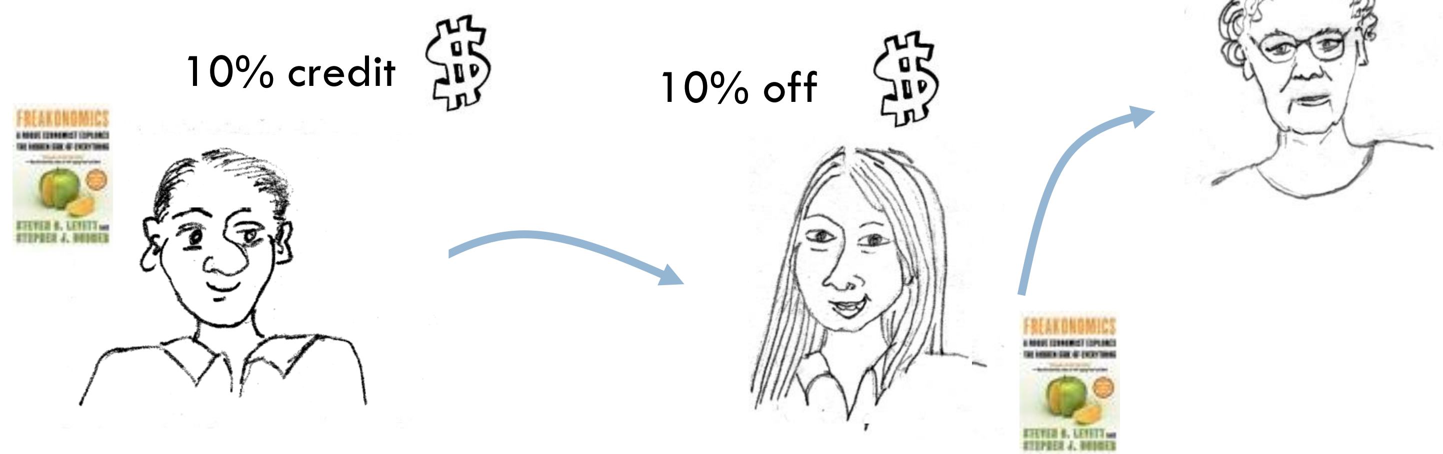
- **Marketing agency** would like you to adopt/buy product *X*
- They estimate the adoption curve



- **Should they expose you to *X* three times?**
- **Or, is it better to expose you *X*, then *Y* and then *X* again?**

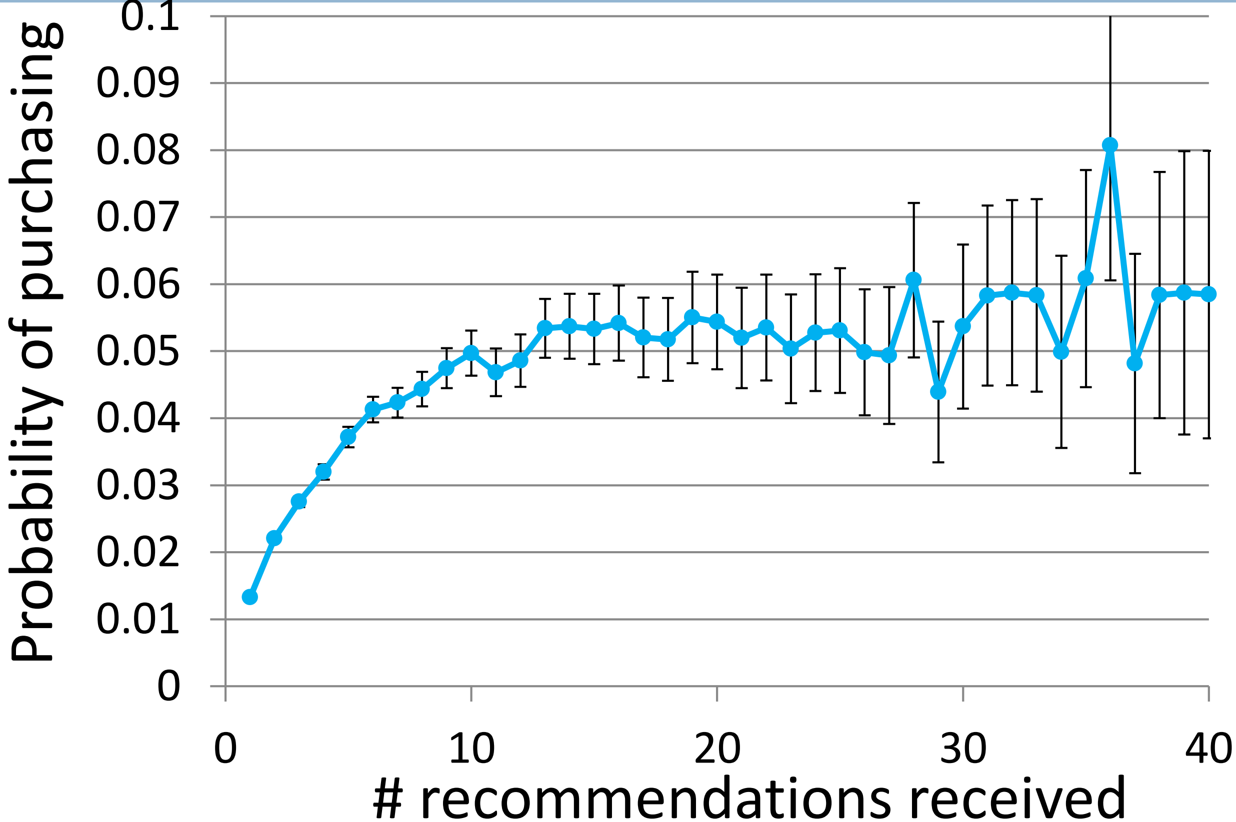
Diffusion in Viral Marketing

- **Senders and followers of recommendations receive discounts on products**



- **Data: Incentivized Viral Marketing program**
  - 16 million recommendations
  - 4 million people, 500k products
  - [Leskovec-Adamic-Huberman, 2007]

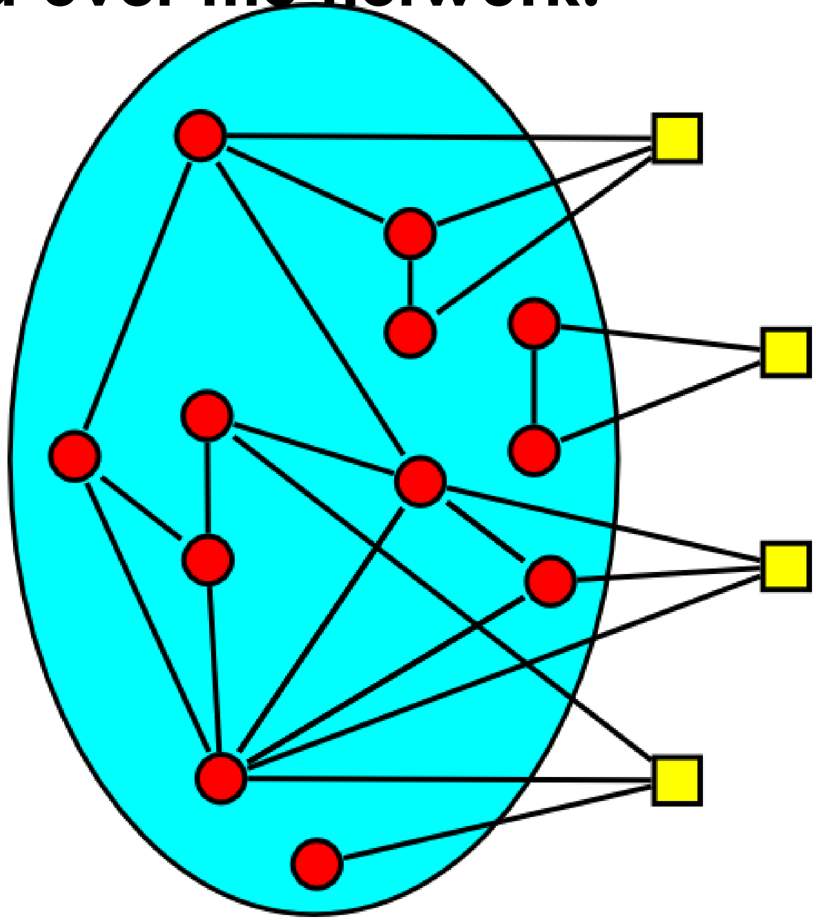
Exposure Curve: Validation



DVD recommendations
(8.2 million observations)

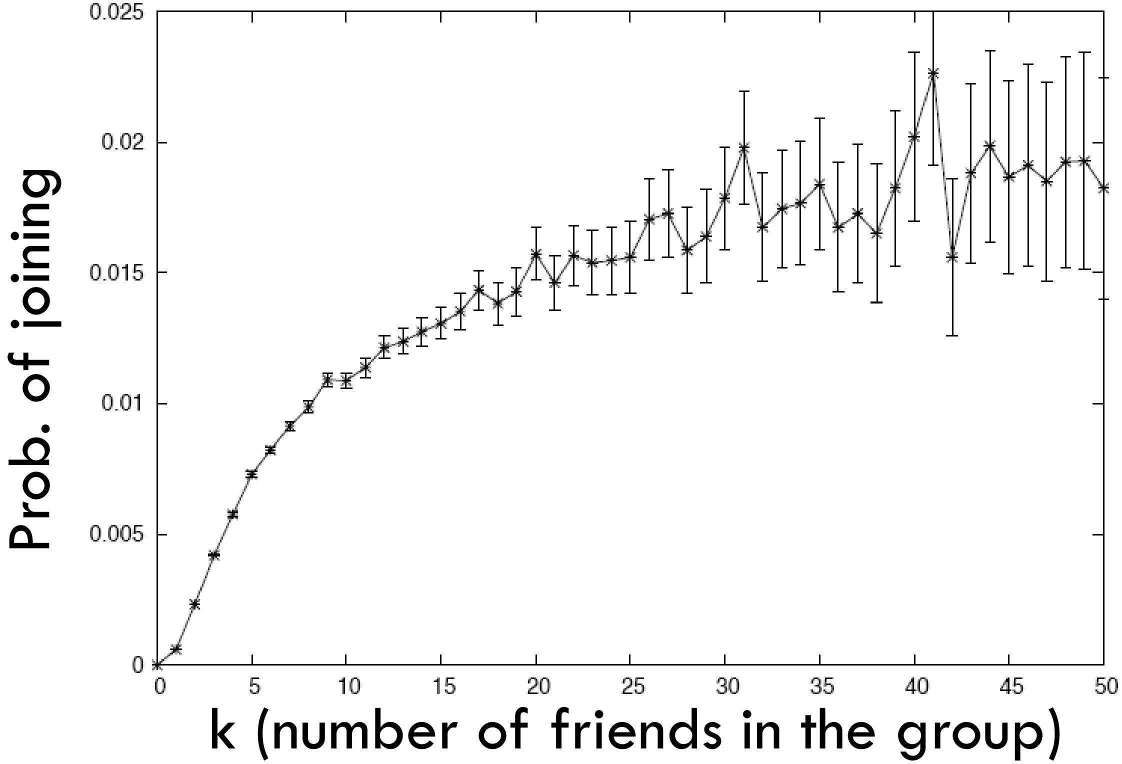
Exposure Curve: LiveJournal

- **Group memberships spread over the network:**
  - Red circles represent existing group members
  - Yellow squares may join
- **Question:**
  - How does prob. of joining a group depend on the number of friends already in the group?



Exposure Curve: LiveJournal

- LiveJournal group membership

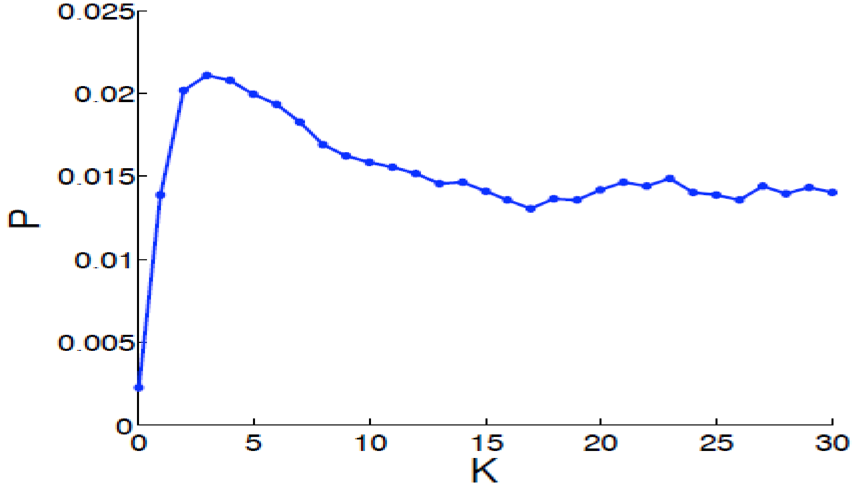


What are We Really Measuring?

- **For viral marketing:**
  - We see that node v receiving the *i*-th recommendation and then purchased the product
- **For groups:**
  - At time t we see the behavior of node v's friends
- **Good questions:**
  - When did v become aware of recommendations or friends' behavior?
  - When did it translate into a decision by v to act?
  - How long after this decision did v act?

Exposure Curve: Information

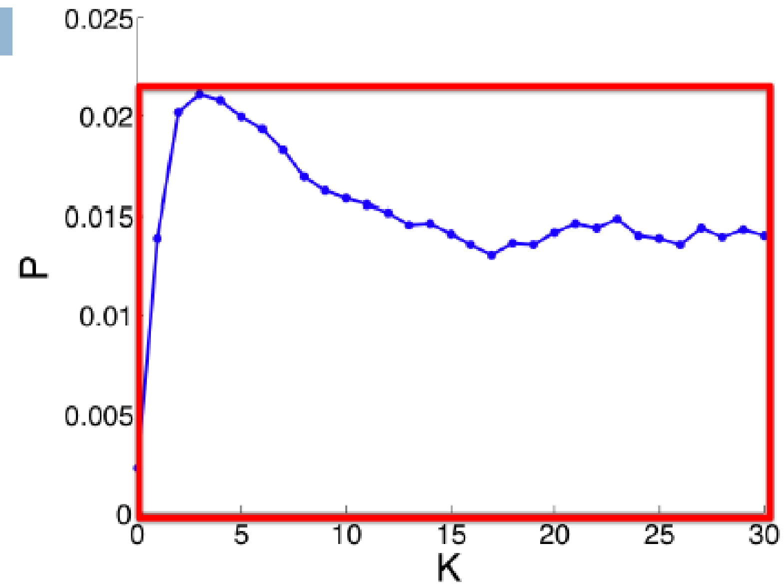
- **Twitter** [Romero et al. '11]
  - Aug '09 to Jan '10, 3B tweets, 60M users

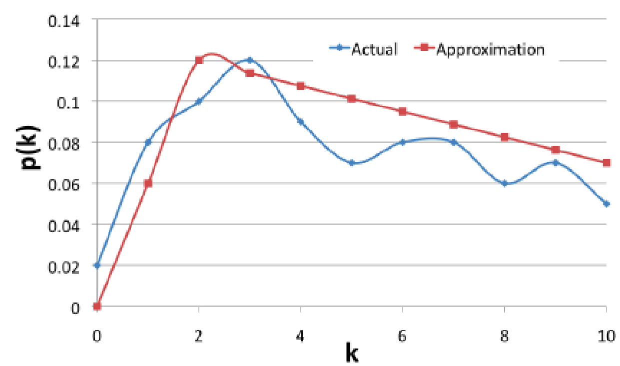


  - Avg. exposure curve for the top 500 hashtags
  - What are the most important aspects of the shape of exposure curves?
  - Curve reaches peak fast, decreases after!

Modeling the Shape of the Curve

- **Persistence of *P*** is the ratio of the area under the curve *P* and the area of the rectangle of length *max(P)*, width *max(D(P))*
  - *D(P)* is the domain of *P*
- **Persistence measures the decay of exposure curves**
- **Stickiness of *P*** is *max(P)*.
- **Stickiness is the probability of usage at the most effective exposure**

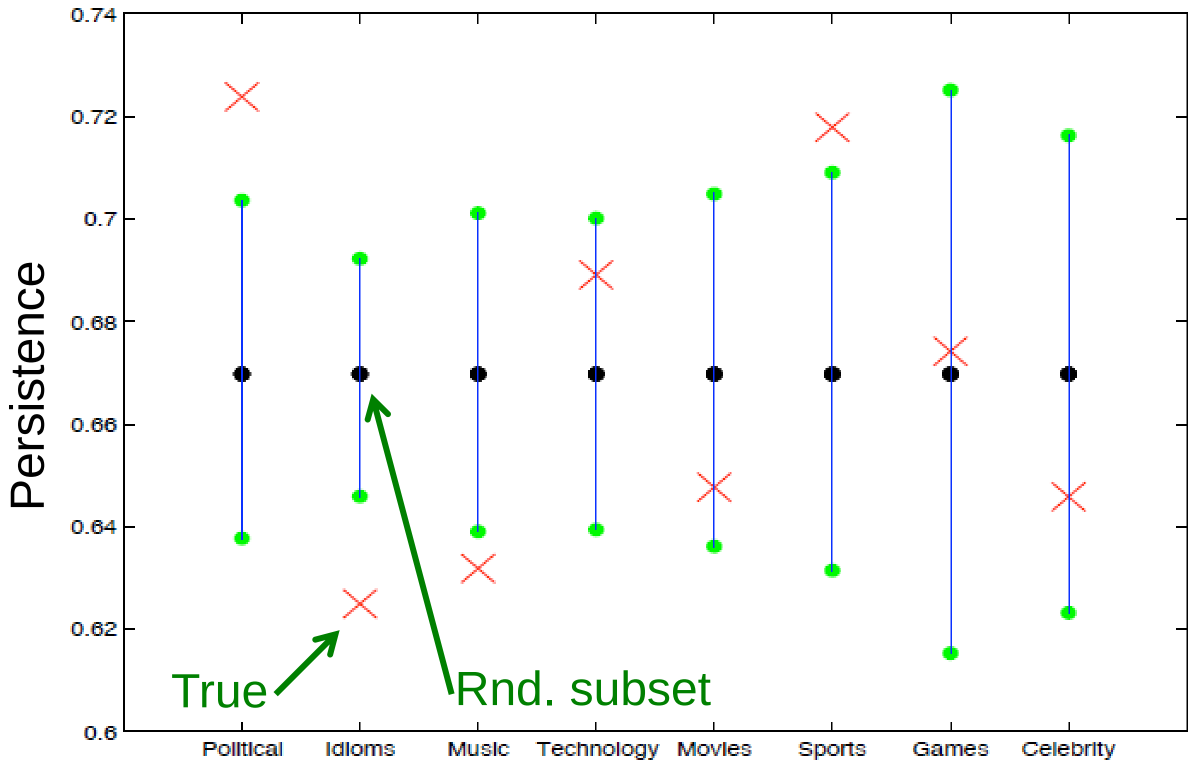




Exposure Curve: Persistence

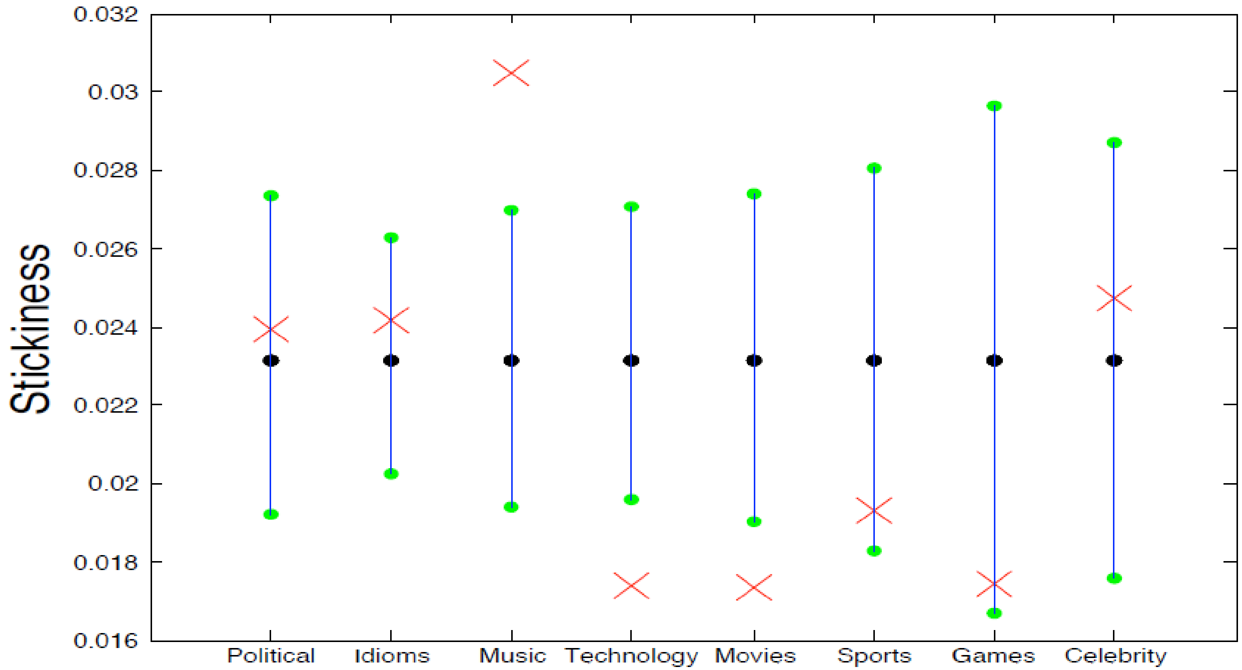
- Manually identify 8 broad categories with at least 20 HTs in each

Category	Examples
Celebrity	mj, brazilwantsjb, regis, iwantpeterfacinelli
Music	thisiswar, mj, musicmonday, pandora
Games	mafiawars, spymaster, mw2, zyngapirates
Political	tcot, glennbeck, obama, hcr
Idiom	cantlivewithout, dontyouhate, musicmonday
Sports	golf, yankees, nhl, cricket
Movies/TV	lost, glennbeck, bones, newmoon
Technology	digg, iphone, jquery, photoshop



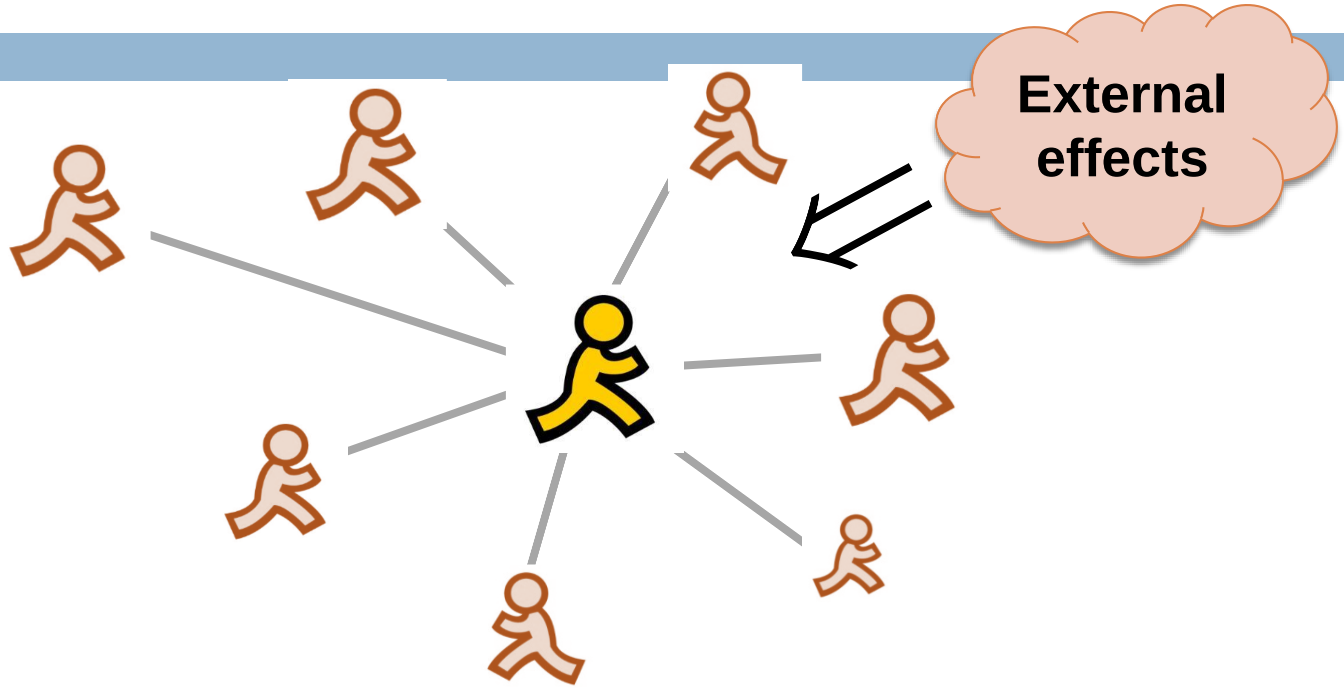
- Idioms and Music have lower persistence than that of a random subset of hashtags of the same size
- Politics and Sports have higher persistence than that of a random subset of hashtags of the same size

Exposure Curve: Stickiness



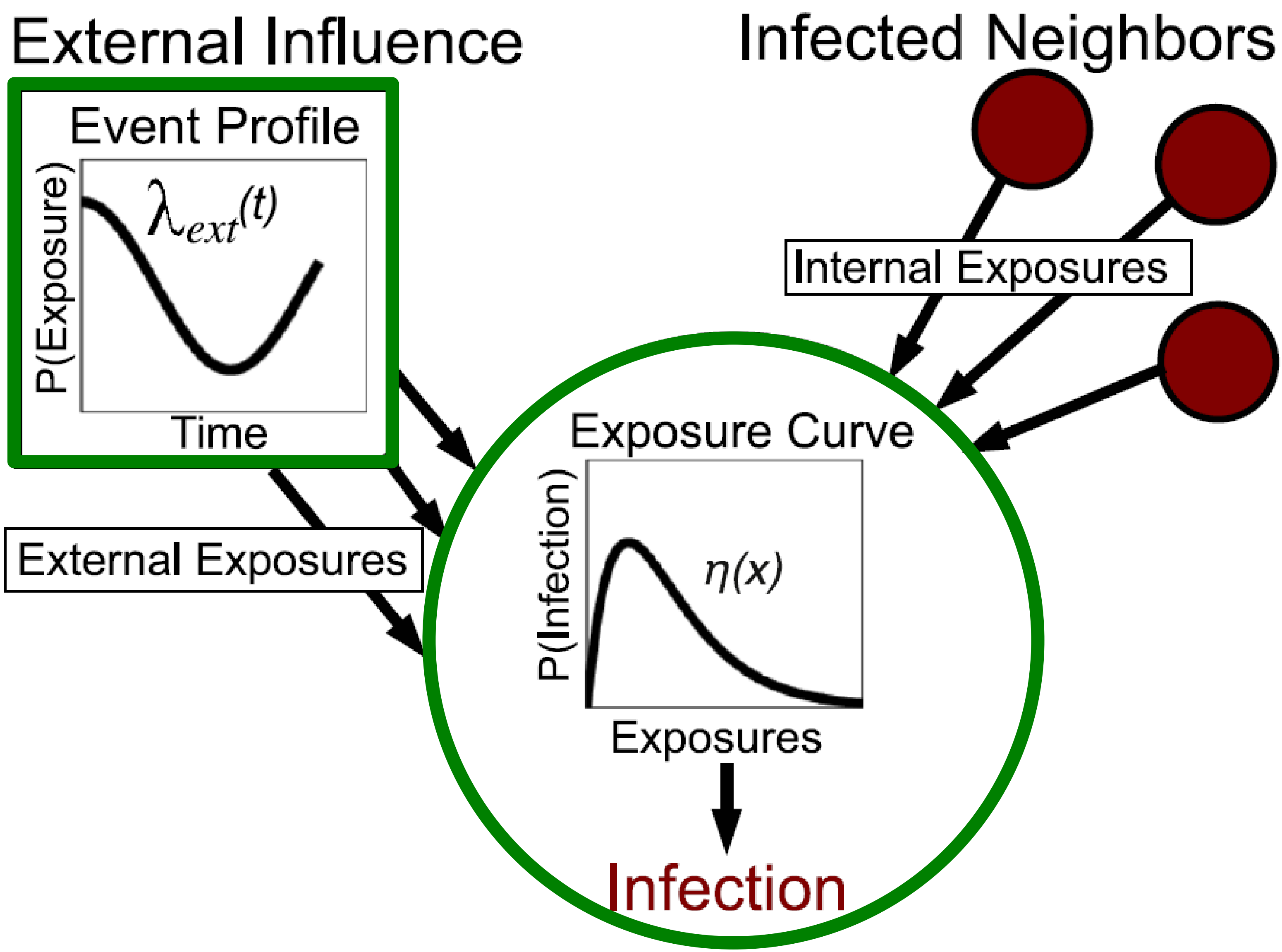
- Technology and Movies have lower stickiness than that of a random subset of hashtags
- Music has higher stickiness than that of a random subset of hashtags (of the same size)

Network & External Exposures

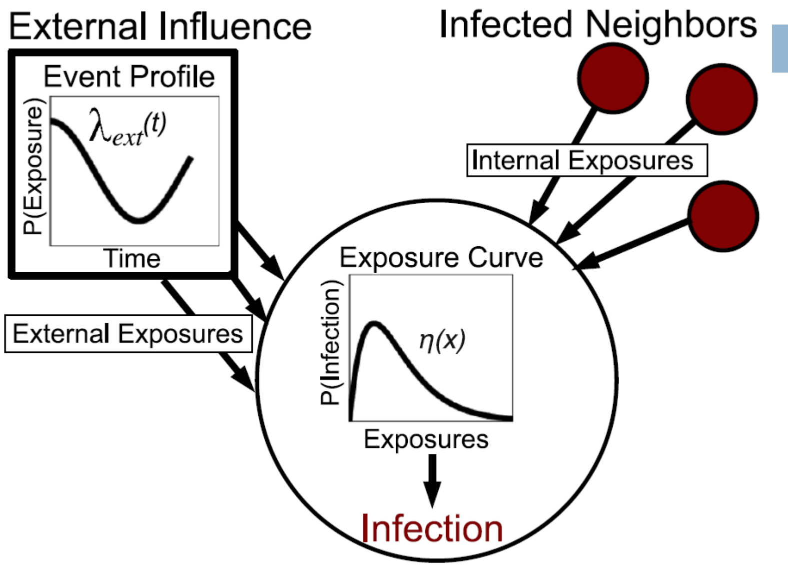


- **Two sources of exposures** *[Myers et al., KDD, 2012]*
  - Exposures from the network
  - External exposures

Putting it all together

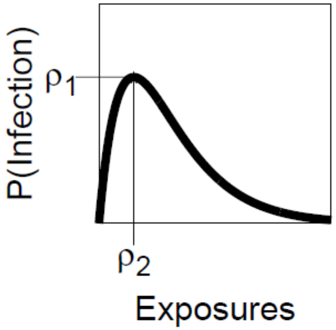


Model Inference Task



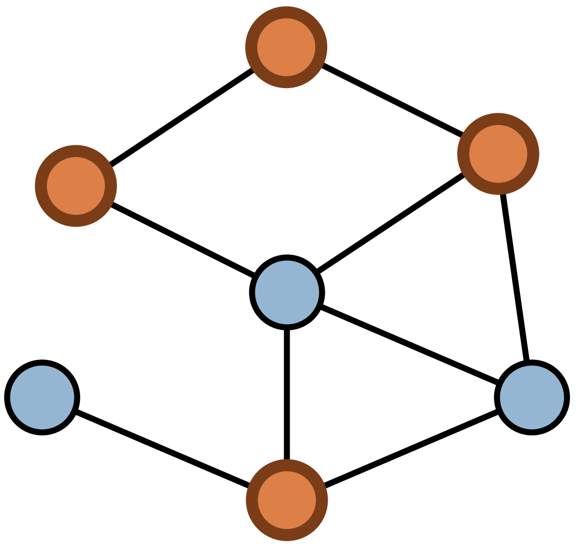
- **Given:**
  - Network G
  - A set of node adoption times *(u, t)* single piece of info
- **Goal: Infer**
  - **External event profile:**

    $\lambda_{ext}(t)$ … # external exposures over time
  - **Adoption curve:**



Experiment

- **In social networks people post links to interesting articles**
  - You hear about an article from a friend
  - You read the article and then post it
- **Data from Twitter**
  - *Complete* data from Jan 2011: 3 billion tweets
  - Trace the emergence of URLs
    - Label each URL by its topic



Results: Different Topics

- **Adoption of URLs across Twitter:**

	max P(k)	k at max P(k)	Duration (hours)	% Ext. Exposures
Politics (25)	0.0007 +/- 0.0001	4.59 +/- 0.76	51.24 +/- 16.66	47.38 +/- 6.12
World (824)	0.0013 +/- 0.0000	2.97 +/- 0.10	43.54 +/- 2.94	26.07 +/- 1.19
Entertain. (117)	0.0015 +/- 0.0002	3.52 +/- 0.28	89.89 +/- 16.13	17.87 +/- 2.51
Sports (24)	0.0010 +/- 0.0003	4.76 +/- 0.83	87.85 +/- 38.03	43.88 +/- 6.97
Health (81)	0.0016 +/- 0.0002	3.25 +/- 0.30	100.09 +/- 17.57	18.81 +/- 3.33
Tech. (226)	0.0013 +/- 0.0001	3.00 +/- 0.16	83.05 +/- 8.73	18.36 +/- 1.80
Business (298)	0.0015 +/- 0.0001	3.18 +/- 0.16	49.61 +/- 5.14	22.27 +/- 1.79
Science (106)	0.0012 +/- 0.0002	4.06 +/- 0.30	135.28 +/- 16.19	20.53 +/- 2.78
Travel (16)	0.0005 +/- 0.0001	2.33 +/- 0.29	151.73 +/- 39.70	39.99 +/- 6.60
Art (32)	0.0006 +/- 0.0001	5.26 +/- 0.66	188.55 +/- 48.17	27.54 +/- 5.30
Edu. (31)	0.0009 +/- 0.0001	3.77 +/- 0.51	130.53 +/- 38.63	21.45 +/- 6.40

- More in *Myers et al., KDD, 2012*