

Week 7.

Spreading Processes on Networks.

- Diseases
- Gossip
- Memes
- Anomalies of neuronal excitations
- Research topics
- Blackouts

[Not Dynamics of networks]

- Continuous vs. Discrete Time
(just like other dynamical systems)

- Simple vs. Complex contagions.



A single exposure may be sufficient for spread.

- Inf. Disease
- Song
- Meme



Multiple exposures required.

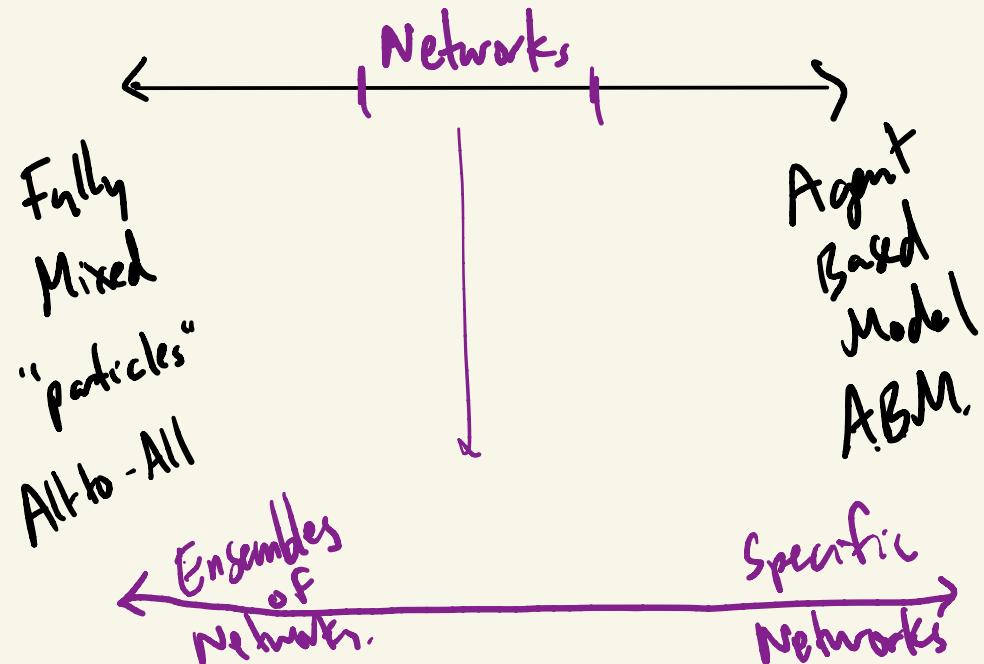
- Art/songs
"acquired taste"
e.g. Greatest Showman
- Candidate
 \hookrightarrow Opinion.
- Fashion.

Two nodes are linked
if they interact in a way
that the disease can spread.

Mechanism Matters



Links are a function
of behavior.



Network + Dynamics

SIX dynamics

Compartmental Models.



Indiv. are in compartments.
Each can be in only one at a time.

① Susceptible
Infected

$$S \rightarrow I$$

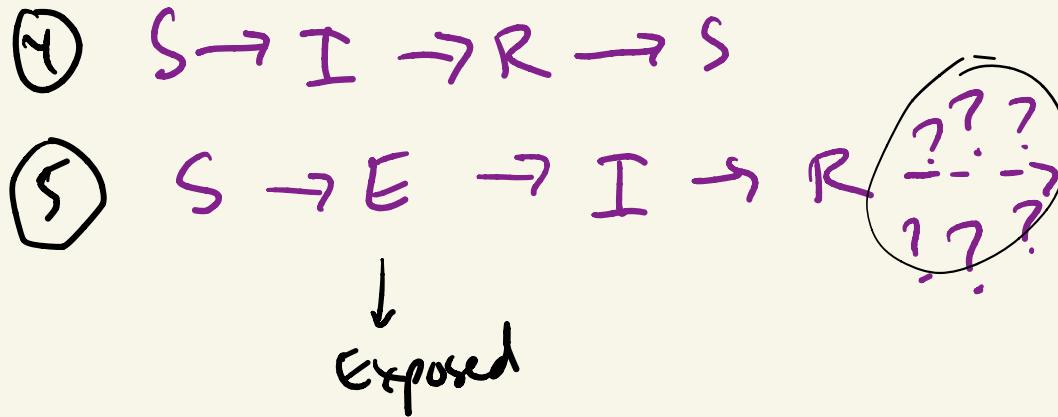
② SIS

$$S \rightarrow I \rightarrow S$$

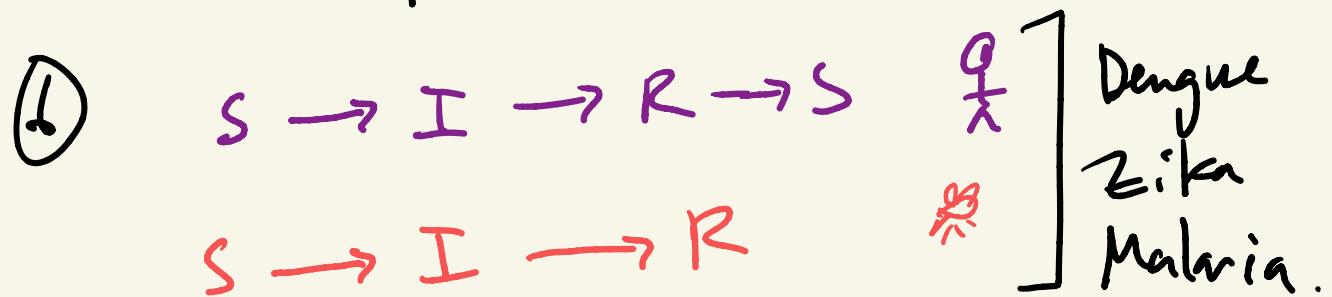
③ SIR

Recovered
"Removed."

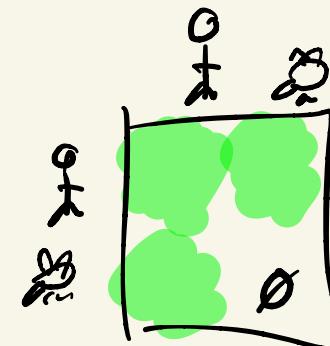
$$S \rightarrow I \xrightarrow{\text{vax.}} R$$



Unknown
for SARS2



Dengue
Zika
Malaria.



The Fully Mixed SIS Model.

- Assumptions: everyone interacts w/ everyone else, in the same way.

Let N be # ppl/nodes.

- An I has a prob. of $\bar{\beta}$ per unit time of transmitting to a S.
- An I has a prob. γ per unit time to heal and become S again.

Bookkeeping.

$$S(t) = \# \text{ susc.}$$

$$I(t) = \# \text{ infecteds.}$$

$$N = S(t) + I(t) \quad \text{const.}$$

$$\frac{I(t)}{N} = \frac{N - S(t)}{N}$$

How does # of S change in a little slice of time?

$$S(t + \Delta t) = S(t) - S(t) \cdot I(t) \bar{\beta} \Delta t + I(t) \gamma \Delta t$$

a little bit later

$$S = \frac{S}{N} \quad i = \frac{I}{N} \quad \beta = \bar{\beta} N$$

① sub in s, i, β

② $s = 1 - i$

③ $\lim \Delta t \rightarrow 0$

New interpretation of β

Exp. # of ppl. that a single infected individual infects per unit time. (if the whole pop is S)

$$\frac{di}{dt} = \beta i(1-i) - \gamma i = \beta(i - i^2) - \gamma i$$

Key Q: Will there be an epidemic at all?

- Assume that i is very small.
- i^2 is so small that we don't care. Neglect it!

↓ linearize

$$\frac{di}{dt} = \beta i - \gamma i$$

$$\frac{di}{dt} = (\beta - \gamma)i$$

When will i grow over time?



$$\beta - \gamma > 0$$

$$\beta > \gamma \quad \frac{\beta}{\gamma} > 1$$

$\frac{\beta}{\gamma}$: epidemic threshold

$$\frac{\beta}{\gamma} < 1$$

no epi.

$$R_0$$

$$\frac{\beta}{\gamma} > 1$$

epi.

key Q: What will be the steady state of $i(t)$?

$$\frac{di}{dt} = 0 \quad \text{no change}$$

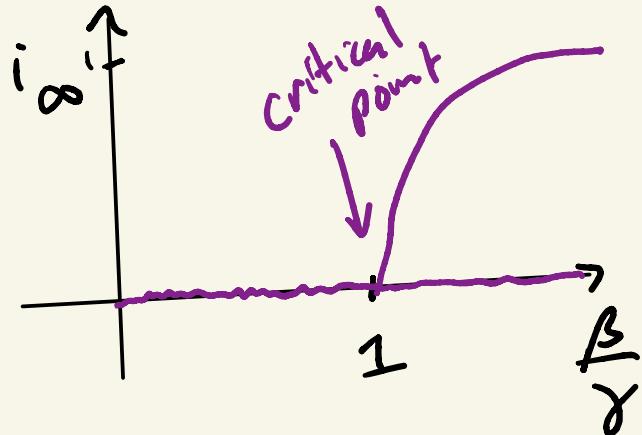
$$\beta(i - i^2) - \gamma i = 0$$

$$\textcircled{1} \quad i = 0$$

$$\textcircled{2} \quad i \neq 0 \quad \beta(1-i) - \gamma = 0$$

$$i_{\infty} = 1 - \frac{\gamma}{\beta}$$

still a fraction.
But it's only > 0
when $\frac{\beta}{\gamma} > 1$



2nd order phase transition
(c.f. Percolation)

All of this \uparrow fully mixed

No Network (unless $A_{ij} = 1 \forall (i,j)$)

Now, let $A_{nm} = 1$ if and only if n, m interact in a disease-transmitting way.

$\bar{\beta}\Delta t = \Pr(\text{inf node passes to an uninfected neighbor})$

$\gamma\Delta t = \Pr(\text{recover})$

Let $i_n(t) = P_r$ that node n is infected at time t .

$i_n(t+\Delta t) =$

- ① n infected at t and did not heal
- OR
- ② n susc. at t and got infected.

$$i_n(t+\Delta t) = i_n(t)[1 - \gamma\Delta t] + (1 - i_n(t))\bar{\beta} \sum_{m=1}^N A_{nm} i_m$$

$$\lim_{\Delta t \rightarrow 0}$$

$$\frac{d i_n}{dt} = -\gamma i_n + (1-i_n) \bar{\beta} \sum_{m=1}^N A_{nm} i_m$$

overall, i small $\Rightarrow i_m$ very small.

$$\frac{d i_n}{dt} = -\gamma i_n + \bar{\beta} \sum_{m=1}^N A_{nm} i_m$$

↓ matrix-vector.

$$\frac{d i_1}{dt} = -\gamma i_1 + \bar{\beta} \sum_m A_{1m} i_m$$

$$\frac{d i_2}{dt} = -\gamma i_2 + \bar{\beta} \sum_m A_{2m} i_m$$

⋮

$$\frac{d i_N}{dt} = -\gamma i_N + \bar{\beta} \sum_m A_{Nm} i_m$$

$$i(t) = \vec{i} e^{(\bar{\beta}\lambda - \gamma)t} ???$$

$$\frac{d \vec{i}}{dt} = (-\gamma I + \bar{\beta} A) \vec{i}$$

$$\frac{d \vec{i}}{dt} = -\gamma \vec{i} + \bar{\beta} A \vec{i}$$

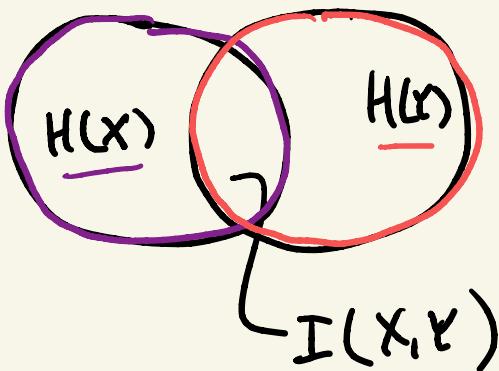
↑

$$\frac{d}{dt} \begin{bmatrix} i_1 \\ i_2 \\ \vdots \\ i_N \end{bmatrix} = -\gamma \begin{bmatrix} i_1 \\ i_2 \\ \vdots \\ i_N \end{bmatrix} + \bar{\beta} \begin{bmatrix} A \end{bmatrix} \begin{bmatrix} i \end{bmatrix}$$

$$NMI(X, Y) = \frac{2 I(X, Y)}{H(X) + H(Y)}$$

mutual information

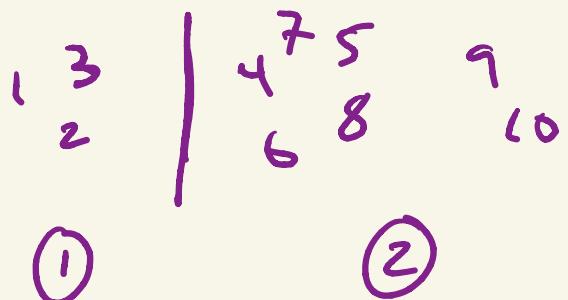
entropy



Imagine that a partition into communities is a random variable X . (another partition is Y).

X communities: group 1: 1, 2, 3
group 2: 4, 5, 6, ..., 10.

What is the entropy of this partition?



$$Pr(1) = \frac{3}{10} \quad Pr(2) = \frac{7}{10}$$

$$X = \left[\frac{3}{10}, \frac{7}{10} \right]$$

categorical distribution
n outcomes

$$H(X) = - \sum_{k=1} P_k \log P_k$$

$$= -\frac{3}{10} \log \frac{3}{10} - \frac{7}{10} \log \frac{7}{10}$$

$$I(X, Y) = - \sum_x \sum_y P_{x,y} \log \frac{P_x P_y}{P_{x,y}}$$

| | |
|---------------|---------------|
| $\frac{1}{6}$ | $\frac{1}{6}$ |
| $\frac{1}{3}$ | $\frac{1}{3}$ |

$\frac{1}{2}$ $\frac{1}{2}$

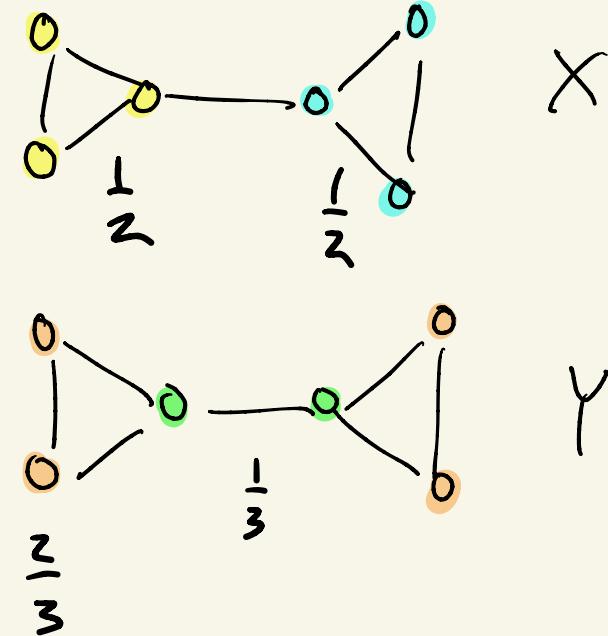
$$= \frac{1}{3}$$

$$\Rightarrow \underline{P_{xy} = P_x P_y}$$

$$\Rightarrow I = 0 \Rightarrow NMI = 0$$

$$I(X, Y) = - \left(\frac{1}{6} \log \frac{\frac{1}{2} \cdot \frac{1}{3}}{\frac{1}{6}} + \frac{1}{3} \log \frac{\frac{1}{2} \cdot \frac{2}{3}}{\frac{1}{3}} \right)$$

If X and Y are totally unrelated.
(indep.)



Confusion matrix

$P(X, Y)$

joint distrib.

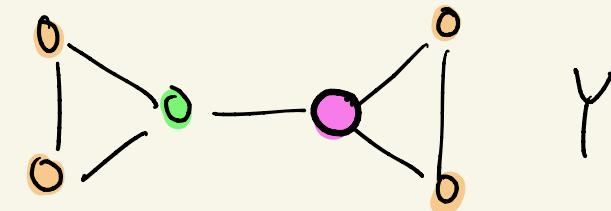
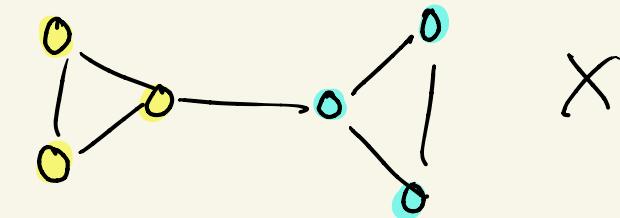
$$NMI(X, Y) = \frac{2I(X, Y)}{H(X) + H(Y)}$$

$$I(X, Y) = - \sum_x \sum_y p_{x,y} \log \frac{p_x p_y}{p_{x,y}}$$



| | | |
|---|---|---------------------------|
| $\begin{matrix} Y_6 \\ Y_3 \\ 0 \end{matrix}$ | $\begin{matrix} 0 \\ Y_3 \\ Y_6 \end{matrix}$ | $\rightarrow \frac{1}{6}$ |
| $\downarrow \frac{1}{2}$ | $\downarrow \frac{1}{2}$ | |
| $\begin{matrix} 0 \\ Y_3 \\ Y_6 \end{matrix}$ | $\begin{matrix} 0 \\ Y_3 \\ Y_6 \end{matrix}$ | $\rightarrow \frac{2}{3}$ |

$$NMI: \frac{2 I(X, X)}{H(X) + H(X)} = 1$$



When $X = Y$, what does the confusion matrix look like?
 → diagonal matrix.

$$I(X, X) = - \sum_x p_{xx} \log \frac{p_x p_x}{p_{xx}}$$

$$= - \sum_x p_x \log p_x = H(X)$$

$$i(t) = \tilde{u} e^{(\bar{\beta}\lambda - \gamma)t} \quad ???$$

$$\frac{di}{dt} = (-\gamma I + \bar{\beta} A) i$$

$i(t) = \tilde{u} e^{(\bar{\beta}\lambda - \gamma)t}$

↑
prob inf.
 \propto eigenvector
centrality!

growth/decay
depends on
 λ , P.F.
eval.

$$\tilde{u} (\bar{\beta}\lambda - \gamma) e^{(\bar{\beta}\lambda - \gamma)t} = (-\gamma I + \bar{\beta} A) \tilde{u} e^{(\bar{\beta}\lambda - \gamma)t}$$

$$\tilde{u} (\bar{\beta}\lambda - \gamma) = (-\gamma I + \bar{\beta} A) \tilde{u}$$

vector scalar matrices vector

$$\cancel{\bar{\beta}\lambda \tilde{u} - \gamma \tilde{u}} = -\gamma \tilde{u} + \bar{\beta} A \tilde{u}$$

$$\cancel{\bar{\beta}\lambda \tilde{u}} = \cancel{\bar{\beta} A \tilde{u}} \quad \bar{\beta} > 0$$

$$\lambda \tilde{u} = A \tilde{u}$$

eval.
 \downarrow
 $M\vec{x} = k\vec{x}$
 $\uparrow \uparrow$
eigenvector

$$i(t) = \bar{u} e^{(\bar{\beta}\lambda - \gamma)t}$$

growth when $\bar{\beta}\lambda - \gamma > 0$

$$\Rightarrow \bar{\beta}\lambda - \gamma > 0$$

$$\bar{\beta}\lambda > \gamma$$

$$\frac{\bar{\beta}}{\gamma} > \frac{1}{\lambda}$$

\uparrow \uparrow
 disease charact. structure of network.

epidemic threshold:

$$\frac{\bar{\beta}}{\gamma} = \frac{1}{\lambda}$$

All-to-All $\beta = \bar{\beta}N$

Now $\beta = \bar{\beta}\langle k \rangle$

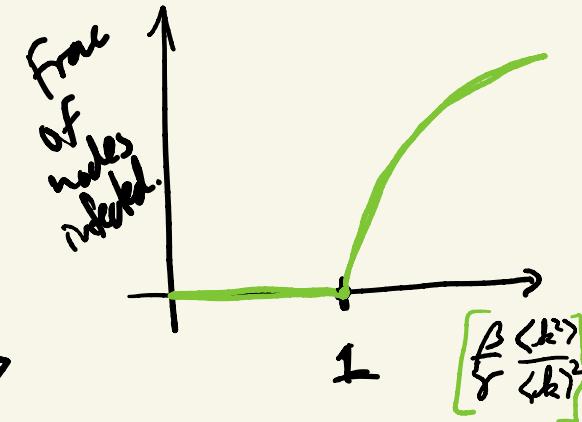
$\beta \sim$ typical # of nodes to become infected at start of epidemic, per infected node, per timestep.

$$\text{e.t. } \frac{\beta}{\gamma} = \frac{\langle k \rangle}{\lambda}$$

For a wide class of networks.

$$\lambda \approx \frac{\langle k^2 \rangle}{\langle k \rangle}$$

$$\frac{\beta}{\gamma} = \frac{\langle k \rangle}{\langle k^2 \rangle}$$



Eigenvalues / Eigenvectors

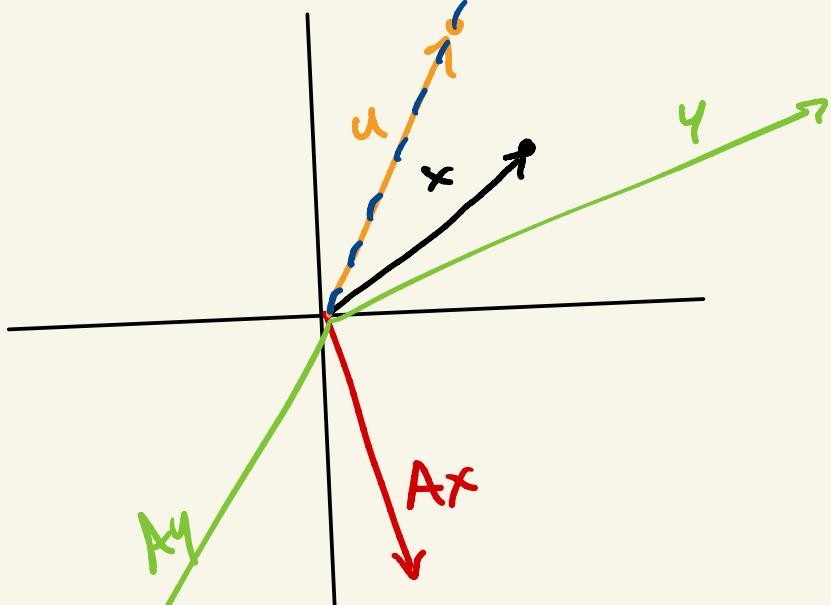
$$A u = \lambda u$$

2×2 \downarrow
 2×1

i
 Au

$$\overbrace{\quad \quad \quad \quad \quad \quad}^{|Au|} = \lambda$$

$\overbrace{\quad \quad \quad \quad}^{|u|}$



Ax is also 2×1

If u represents P vector of infected nodes.

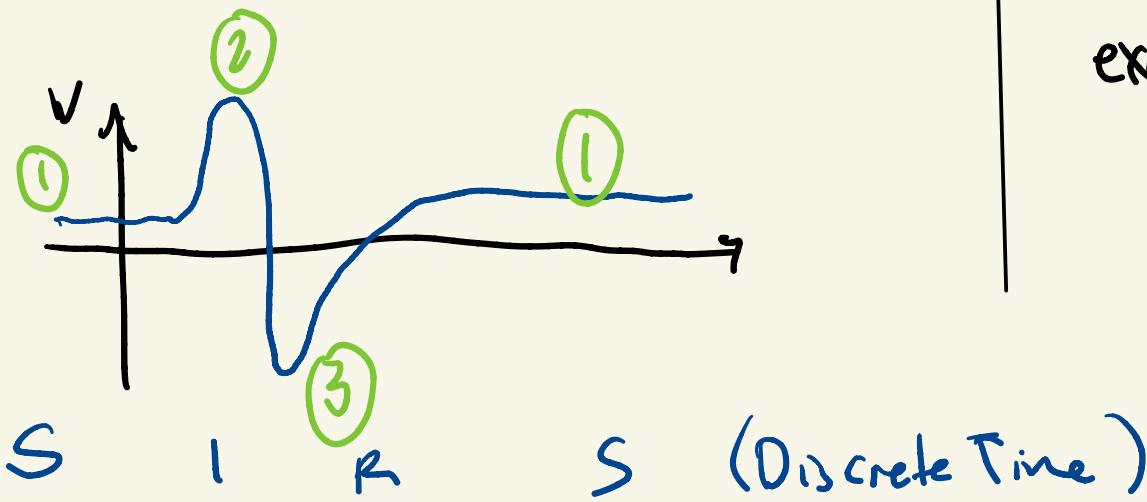
$\Rightarrow Au = \lambda u$ represents stretched version of those probabilities.
“Direction of growth” for infections.

$$i(t) = \bar{u} e^{(\bar{\beta}\lambda - \gamma)t}$$

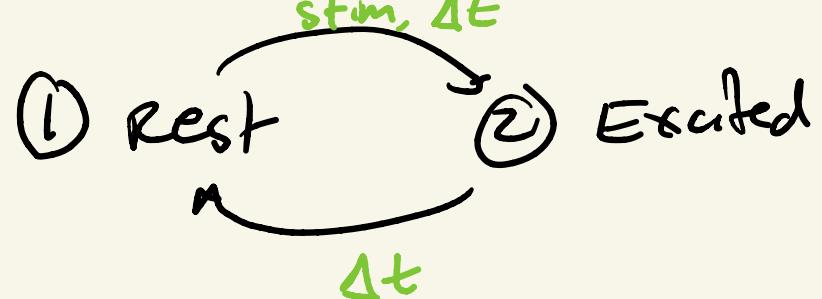
Excitable Dynamics

Greenberg-Hastings
Cellular Automaton.

- ① Resting stimulus!
- ② Excited deterministic
- ③ Refractory (recovering - neither excited nor excitable)



Let there be 0 refractory states.



Consider a weighted network.

$A_{nm} = \text{Pr. that excited } n$
transmits stimulus to resting m

A is a weighted, directed adj. matx.

Let $p_m(t) = \text{Pr. that node } m \text{ is}$
excited at time t .

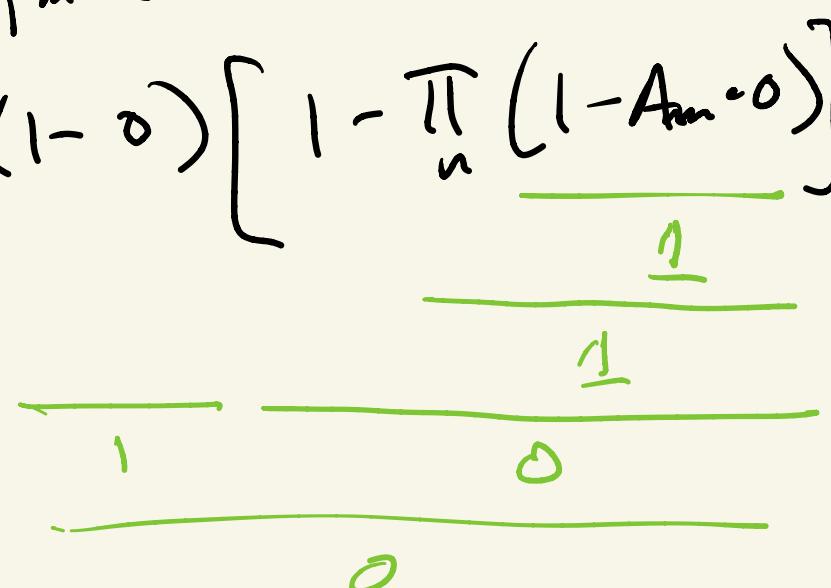
$$p_m(t+1) = \underbrace{(1-p_m(t))}_{\text{must have been at } t \text{ resting}} \left[1 - \prod_n (1 - A_{nm} p_n(t)) \right]$$

- must have been at t resting
- And got a stimulus from a nbr.

What are the fixed points of this dynamics?

$$\vec{p} = \vec{0} \quad \text{check } p_m = 0 \text{ for } m$$

$$0 = (1-\alpha) \left[1 - \prod_n (1 - A_{nm} \cdot 0) \right]$$



$\Pr(\text{stim by a nbr})$

$$= 1 - \Pr(\text{not stim by any of its nbrs})$$

$$= 1 - \prod_{\substack{\text{nbrs} \\ n}} \Pr(\text{not stim by } n)$$

$$= 1 - \prod_{\substack{\text{nbrs} \\ n}} (1 - \Pr_{\text{was stim by } n})$$

$$P_m(t+1) = (1 - p_m(t)) \left[1 - \prod_n (1 - A_{nm} P_n(t)) \right] \quad (1-x)(1-x)(1-x)\dots$$

$$1 - 3x + \mathcal{O}(x^2)$$

p_m small. $\rightarrow p_m P_n$ too small
to care about!

$$P_m(t+1) = \left[1 - \prod_n (1 - A_{nm} P_n(t)) \right]$$

$$-p_m(t) \left[1 - \prod_n (1 - A_{nm} P_n(t)) \right] \quad \mathcal{O}(p^2)$$

c
↓
Linearize
↓

$$P_m(t+1) = \sum_n p_n(t) A_{nm}$$

Ansatz. Let $P_m(t) = u_m \lambda^+$

$$\frac{(1 - A_{p_1})(1 - A_{p_2})(1 - A_{p_3})\dots(1 - A_{p_r})}{1 - \sum A_{nm} P_n(t)} + \mathcal{O}(p^2)$$

$$\uparrow \quad u_m \lambda^{t+1} = \sum_n u_n \lambda^+ A_{nm}$$

$$u_m \lambda = \sum_n A_{nm} u_n$$

$$\lambda u = A^+ u \quad \text{Eigenvalue Equation.}$$

$$A_u = \lambda u$$

$$\underline{P_m(t) = u_m \lambda^t}$$

① Pr node m is excited is prop. to. eigenvector centrality! u_m

② Stability.

Growth: $\lambda > 1$

Decay: $\lambda < 1$

Dynamical importance.

Juan G.
↓
APPM.

Restrepo, Okt, Klunt. goes like eigen. centrality.

G. H. C. A.

- discrete time

- excitable dynamics

\Rightarrow growth dep. on λ .

\Rightarrow node heterogeneity in R_e (excited) goes like eigen. centrality.

SIS

- cont. time

- inf. dynamics

\Rightarrow growth dep. on λ .

\Rightarrow node heterogeneity in R_i (infected)

$$\frac{\beta}{\gamma} \frac{\langle k^2 \rangle}{\langle k \rangle^2}$$

\downarrow disease \downarrow contact network.

Greedy Mod Max!

1) Consider all possible Merges.

2) compute \hat{Q} that or ΔQ would result.

3) Choose best.

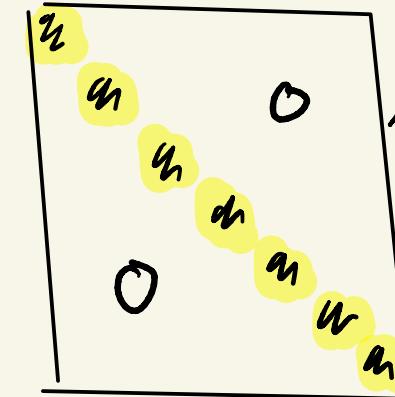
4) Implement that best merge

$$I(X, Y) = - \sum_x \sum_y p_{x,y} \log \frac{p_x p_y}{p_{x,y}}$$

What if $X = Y$?

$$I(X, X) = - \sum_x \sum_{x'} p_{x,x'} \log \frac{p_x p_{x'}}{p_{x,x'}}$$

States of x'



States of x

square.

$$\text{NME} = \frac{2 I_{xx}}{H_x + H_y} = \frac{2 H_x}{H_x + H_x} = 1$$

$$I(X, X) = - \sum_x p_{xx} \log \frac{p_x p_x}{p_{xx}}$$

$p_{xx} = p_x$

$$= - \sum_x p_x \log \frac{p_x}{p_x} = H(X)$$

October 9, 2020

- HW due tonight!
- Project proposals due tonight!
 - 1 per group.
 - All names on proposal.

Granovetter Threshold Model, 1978

- N people in a crowd
- Each person i has a threshold θ_i above which they will participate.
 - $f(x)$ # of people w/ threshold = x PNF
 - $F(x)$ # of people w/ threshold $\leq x$ CDF
 - $s(t) = \#$ of people participating at time t .

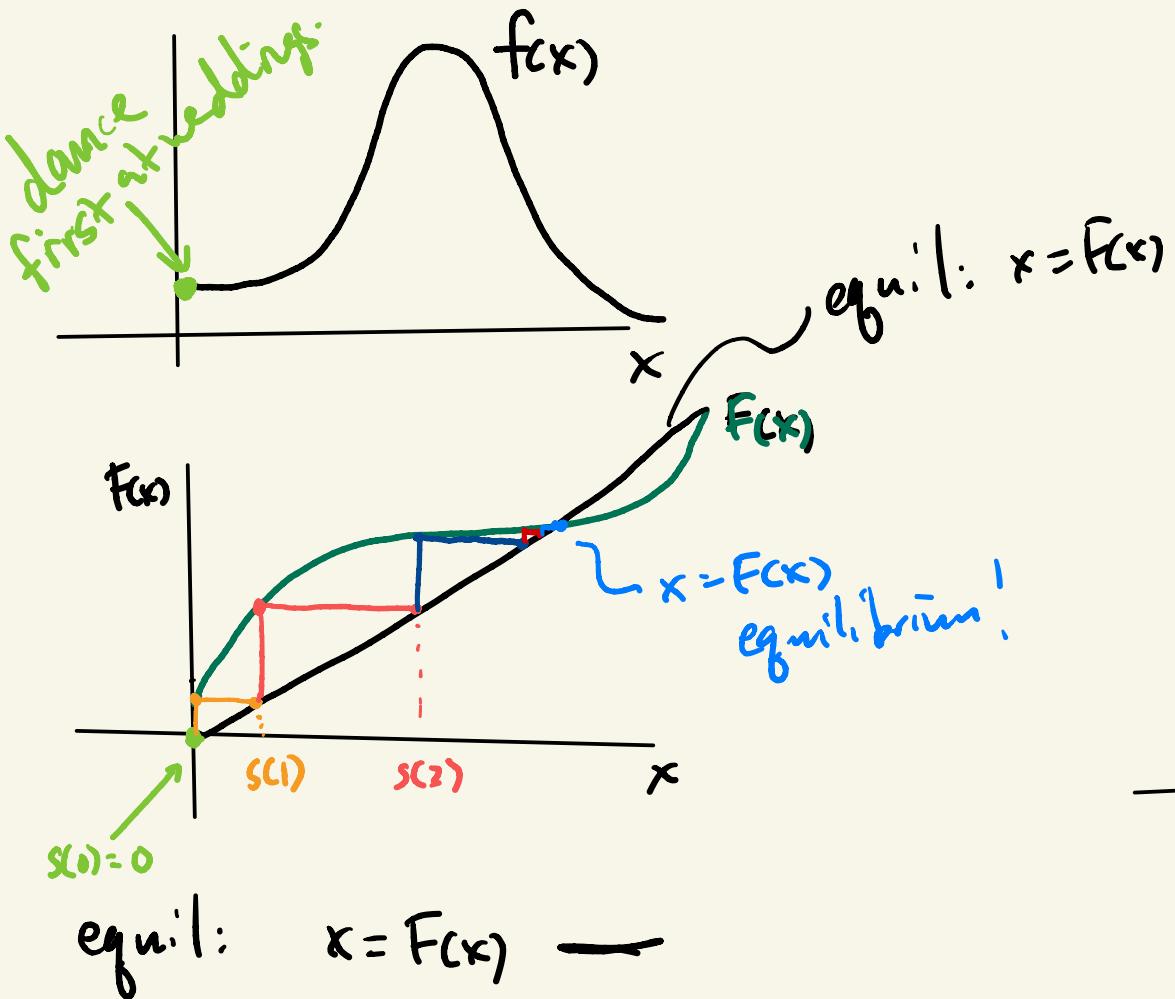
$$s(0) = 0$$

$$\begin{aligned}s(1) &= \# \text{ ppl. w/ threshold } \leq 0 \\ &= F(0)\end{aligned}$$

$$s(2) = F(s(1)) = F(F(0))$$

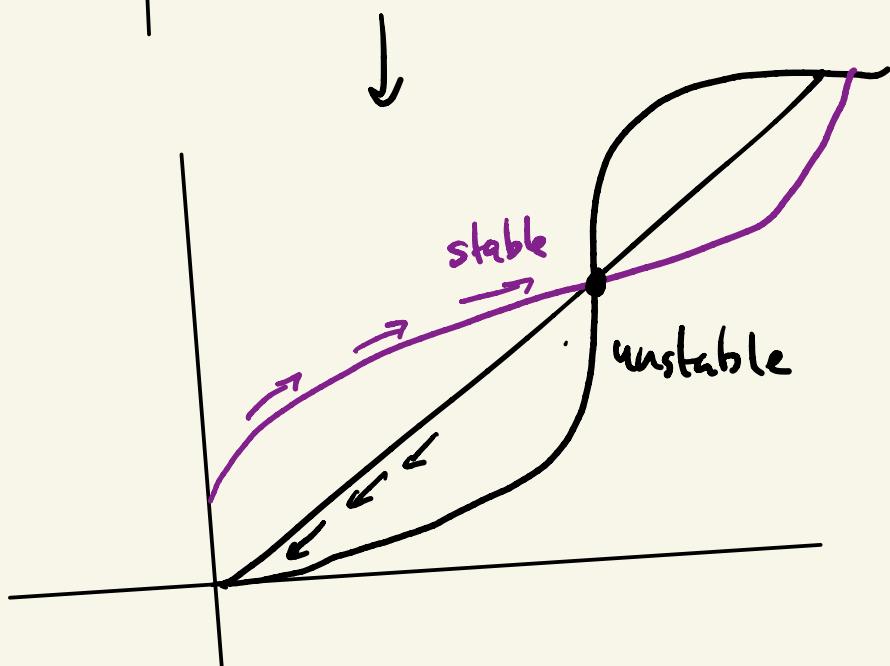
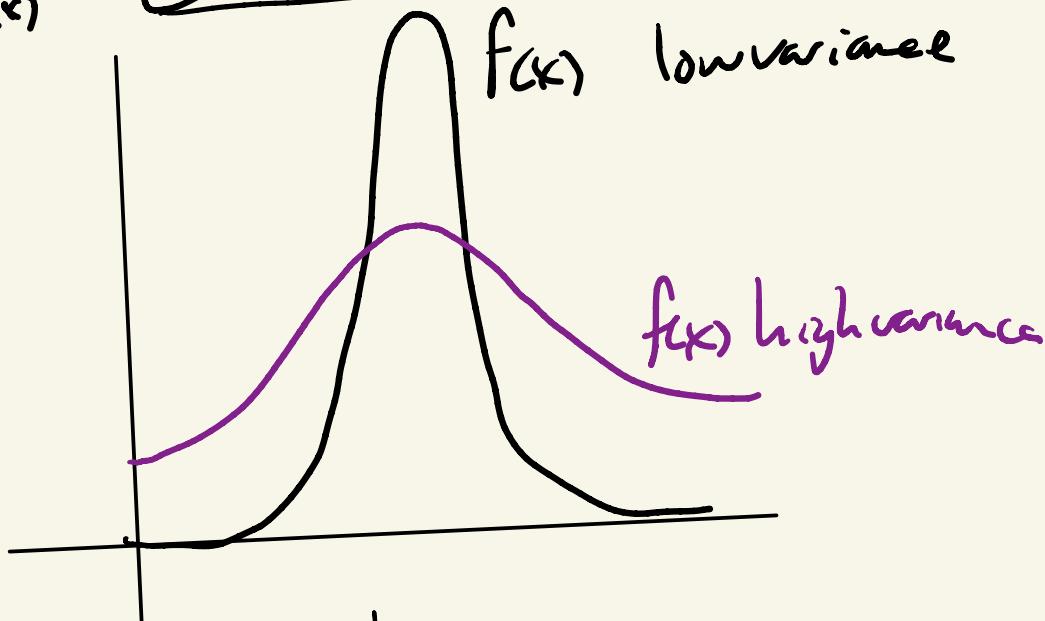
$$s(t+1) = F(s(t))$$

$$\Rightarrow \text{steady state: } s(t) = F(s(t))$$



When do we get a root?

↑ Variance of thresholds
 \Rightarrow
 growth in participation



What about Cascade
Models on a network?

(Kleinberg)

Networked Coordination Games

Behaviors A
"old"
B
"new"

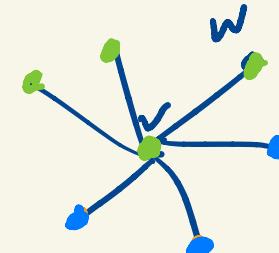
In the network, nodes have an
incentive to have behaviors match.

$$0 < q < 1$$

If v, w both A $\rightarrow q$

v, w both B $\rightarrow 1-q$

v, w opposite $\rightarrow 0$



$$Avw = 1 \text{ (neighbor)}$$

What should v do?
(to max its payoff)

If node v has deg d_v ,
and d_v^A nbrs are A
 d_v^B nbrs are B

- Payoff from choosing A is $d_v^A q$
- Payoff from choosing B is $d_v^B (1-q)$

$$d_v^A = d_v - d_v^B$$

$$\frac{(d_v - d_v^B)q}{d_v} < \frac{d_v^B(1-q)}{d_v}$$
$$d_v q < d_v^B \quad q < \frac{d_v^B}{d_v}$$

fraction
of nbrs
w/ B

A node should convert $A \rightarrow B$
when at least a fraction q
of its nbrs have converted!

When does B spread?

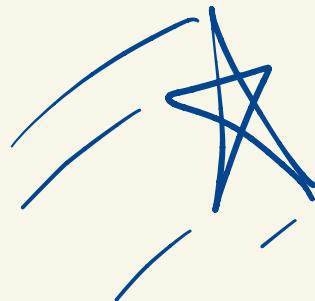
S initial set of converted.

- After one round, w/ threshold q ,
 $h_q(S)$ are now converted.
- $h_q^k(S)$ is the set of converted
nodes after k rounds.

NB: nodes can switch $A \rightarrow B$ AND $B \rightarrow A$.

- A node w is converted by a set S if for some k^* we have $w \in h_q^{k^*}(S)$ & $k^* \geq k^*$.
(w gets converted and never goes back)

- A set S is contagious w.r.t. h_q
if every node is converted by S .
- What is the maximum q for
which there exists a contagious set?



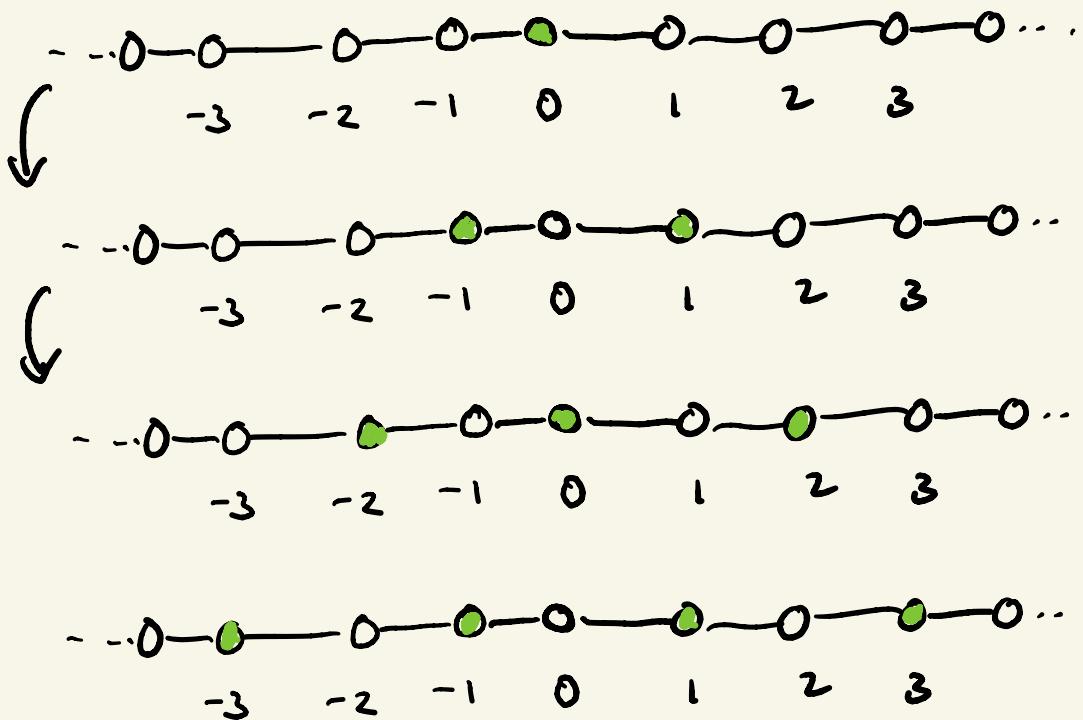
Kleinberg.

↓
Textbook:

- Networks, Graphs, Markets

G:

New thang! B $g = \frac{1}{2}$

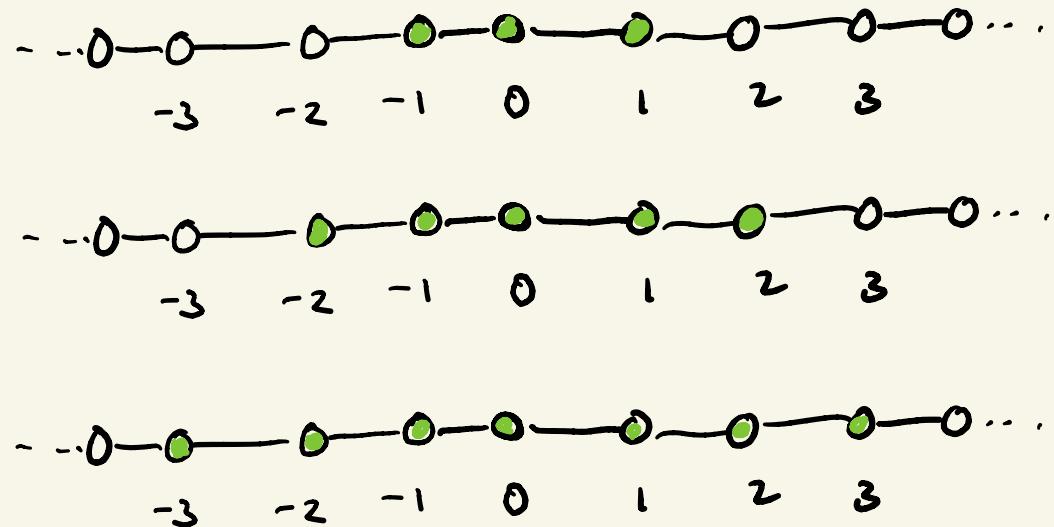


Alternating, on/off, A/B, ... forever.

No Node is converted! Oscillate forever.

$\{-3, 0, 3\}$ not contagious for $g = \frac{1}{2}$

adopt if: $g \leq \frac{d\psi}{dv}$



$\{-1, 0, 1\}$ is contagious
at $g = \frac{1}{2}$

In fact, $\frac{1}{2}$ is this graph's
contagion threshold.

Any graph, contagion threshold
must be at least $\frac{1}{2}$.

Does there exist any graph w/ a contagion threshold $> q$?

(1) JK describes "progressive" and "non-progressive" versions of the dynamics.

$$A \rightarrow B, B \rightarrow A$$

$$A \rightarrow B$$

(2) Progressive dynamics and non-progressive dynamics must have the same threshold!

'magic'

(3) Show that contagion threshold is, at most, $\frac{L}{2}$,

for any progressive dynamics . . .

By (2) \Rightarrow same threshold hold for non-progressive dynamics.

Cascading Behavior in Networks