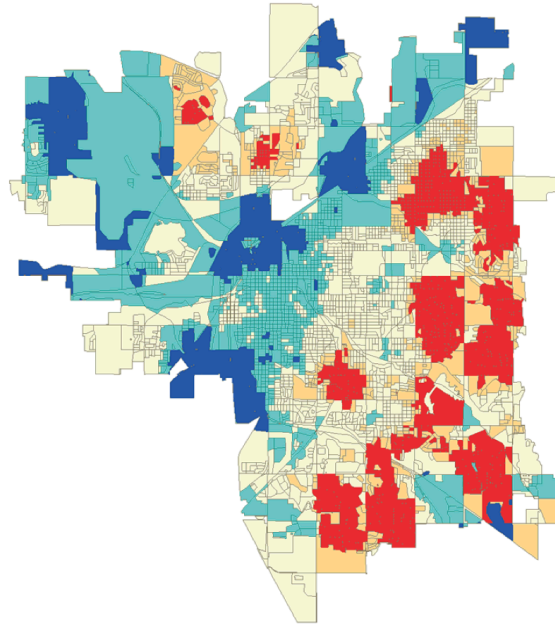
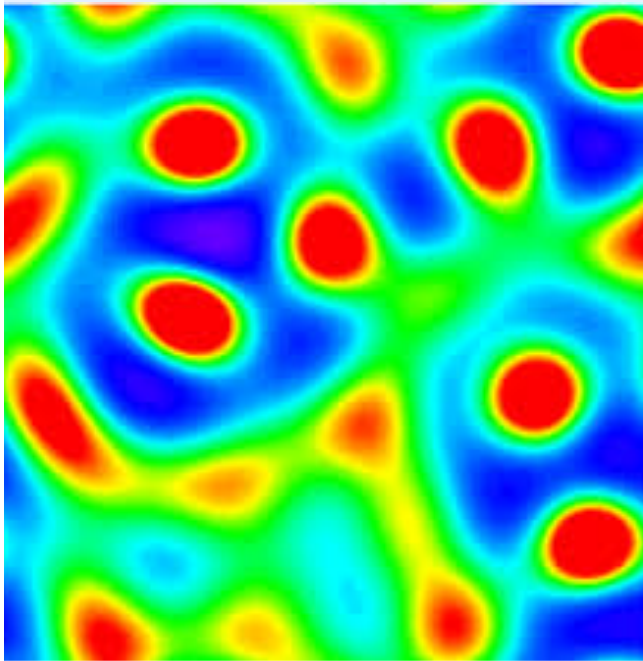


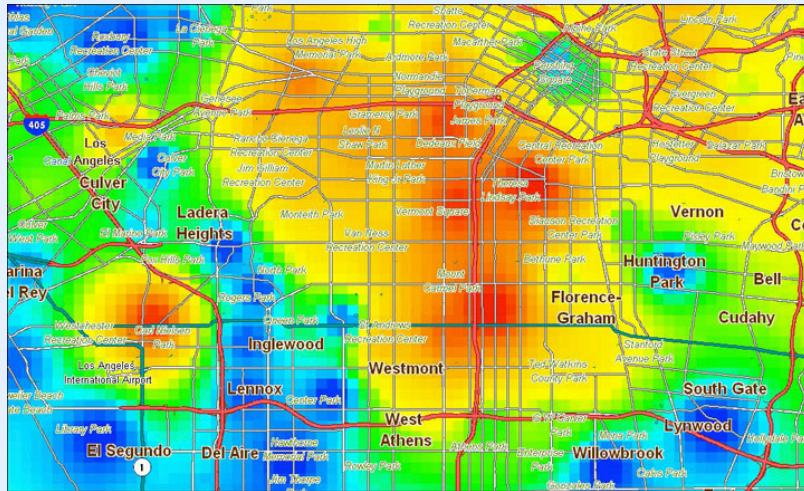
Case studies from mathematical models of criminal behavior



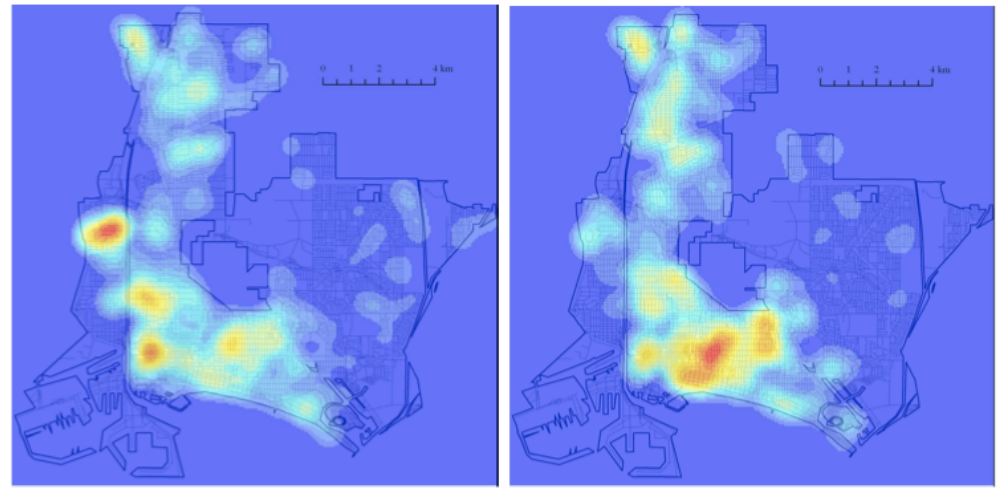
Maria R. D'Orsogna, Dept. Mathematics CSUN

1. Crime hotspots
2. An informant and a criminal
3. Recidivism and rehabilitation policies
4. Criminal networks

1. Crime Hotspots



GTA, Los Angeles



Residential burglary, Long Beach

Spatio-temporal clusters of crime

Burglary, grand theft auto

Time scales: hours to months

Geographical scales: a few city blocks

Broken Windows effect



Crime generates
more and worse
crime

“Consider a building with a few broken windows. If the windows are not repaired, the even tendency is for vandals to break a few more windows. Eventually, they may even break into the building, and if it’s unoccupied, perhaps become squatters or light fires inside. Or consider a sidewalk. Some litter accumulates. Soon, more litter accumulates. Eventually, people start leaving bags of trash from take-out restaurants there or breaking into cars.”

James Wilson and George Kelling, Atlantic Monthly 1982

Routine Activity Theory

“I always go back to the same places because, one you been there, you know just about when you been there before and when you can go back. And every time I hit a house, it’s always on the same day of the week.”

SOCIAL CHANGE AND CRIME RATE TRENDS: A ROUTINE ACTIVITY APPROACH*

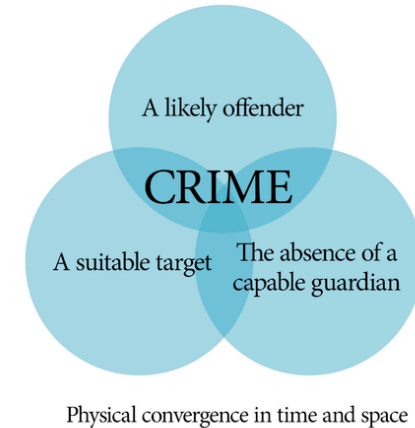
LAWRENCE E. COHEN AND MARCUS FELSON

University of Illinois, Urbana

American Sociological Review 1979, Vol. 44 (August):588–608,

In this paper we present a “routine activity approach” for analyzing crime rate trends and cycles. Rather than emphasizing the characteristics of offenders, with this approach we concentrate upon the circumstances in which they carry out predatory criminal acts. Most criminal acts require convergence in space and time of *likely offenders*, *suitable targets* and the *absence of capable guardians* against crime. Human ecological theory facilitates an investigation into the way in which social structure produces this convergence, hence allowing illegal activities to feed upon the legal activities of everyday life. In particular, we hypothesize that the dispersion of activities away from households and families increases the opportunity for crime and thus generates higher crime rates. A variety of data is presented in support of the hypothesis, which helps explain crime rate trends in the United States 1947–1974 as a byproduct of changes in such variables as labor force participation and single-adult households.

ROUTINE ACTIVITY THEORY



Repeat victimization

Figure 1:
Time Course Between Repeat Commercial Burglaries
Montgomery County, MD

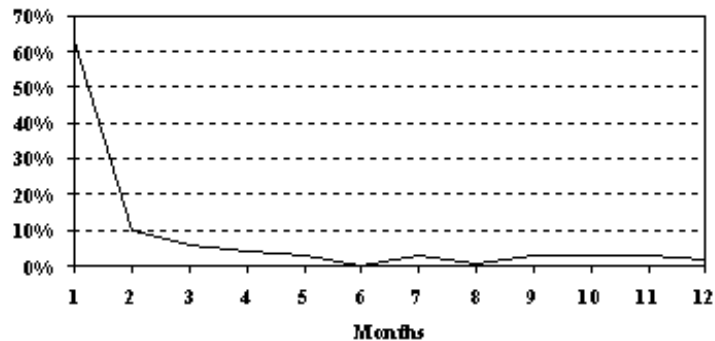
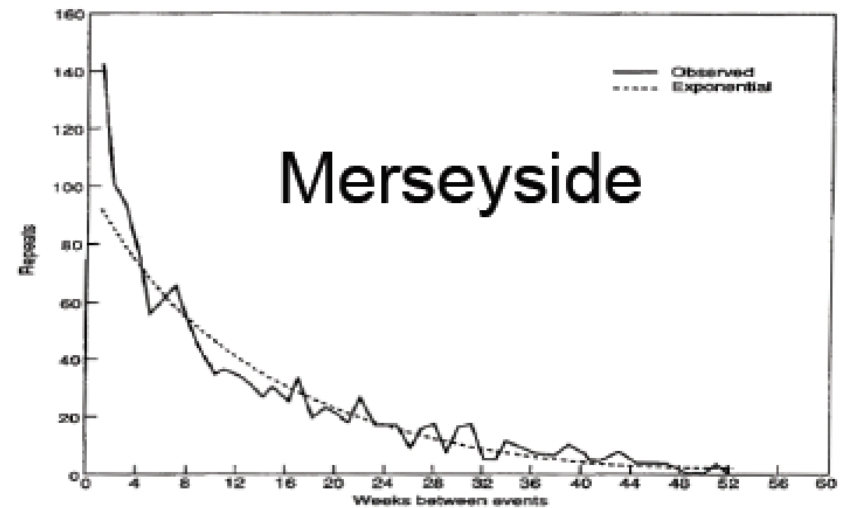
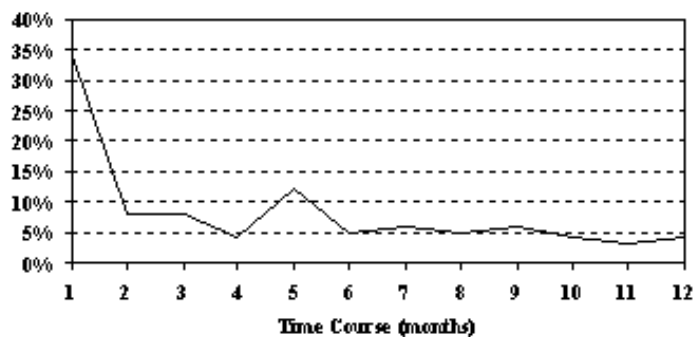
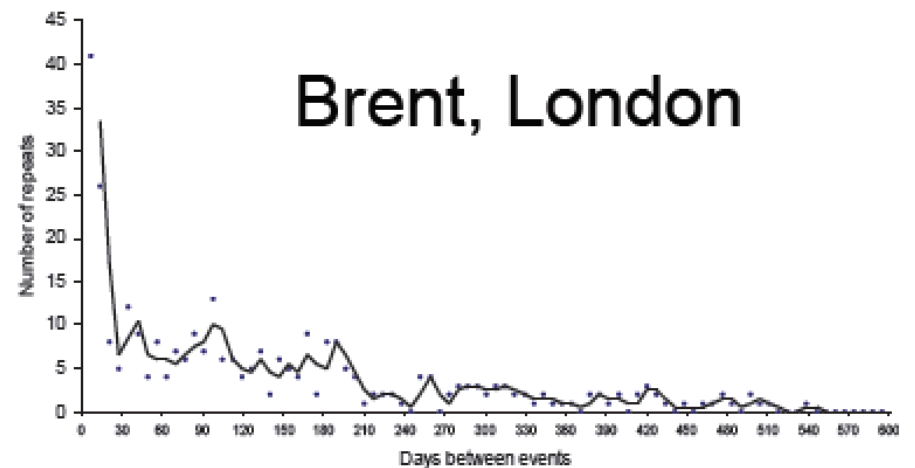


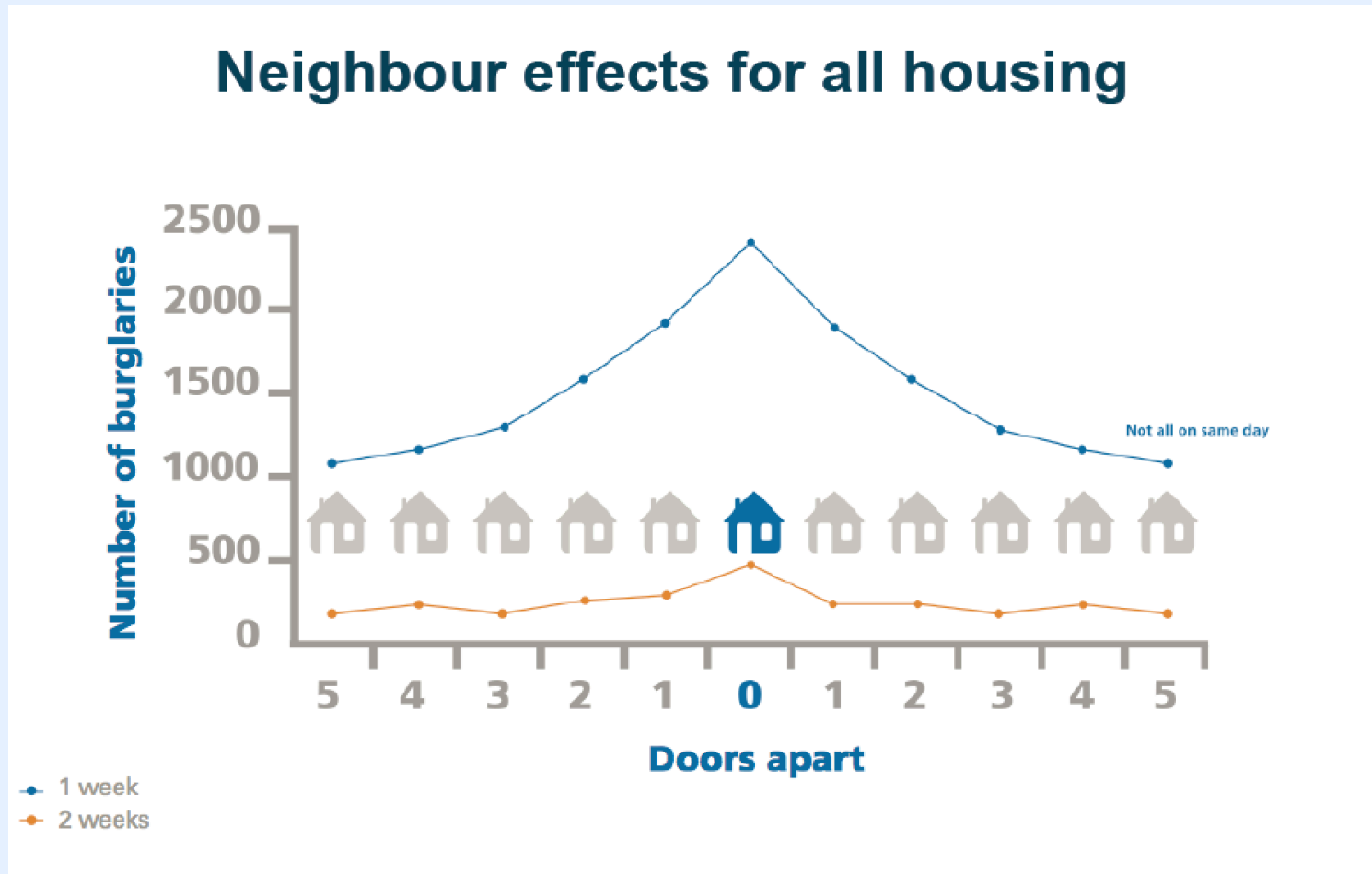
Figure 2
Time Course Between Repeat Commercial Burglaries:
Indianapolis, IN



Temporal decay of residential burglary revictimisation over a 19 month period.

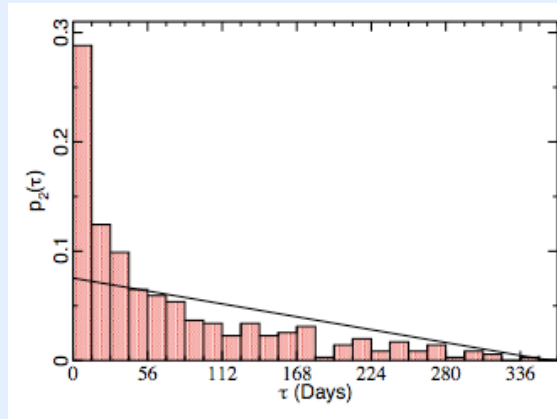


Your neighbors are at risk as well!

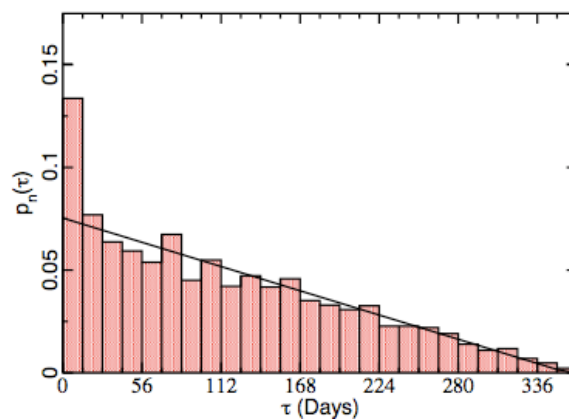


Bowers, K.J., and Johnson, S.D. (2005).
European Journal of Criminology, 2(1), 67-92.

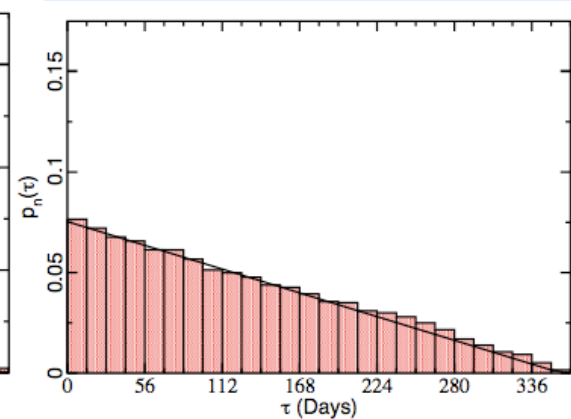
Residential burglary, Long Beach



0 meters



100 meters



4000 meters

Repeat and Near-repeat burglaries within one year

If random, repeat burglary probability within D days is

$$p_2(t) = \frac{2(D-t)}{D(D+1)}$$

Repeat burglary probability is higher at short distances

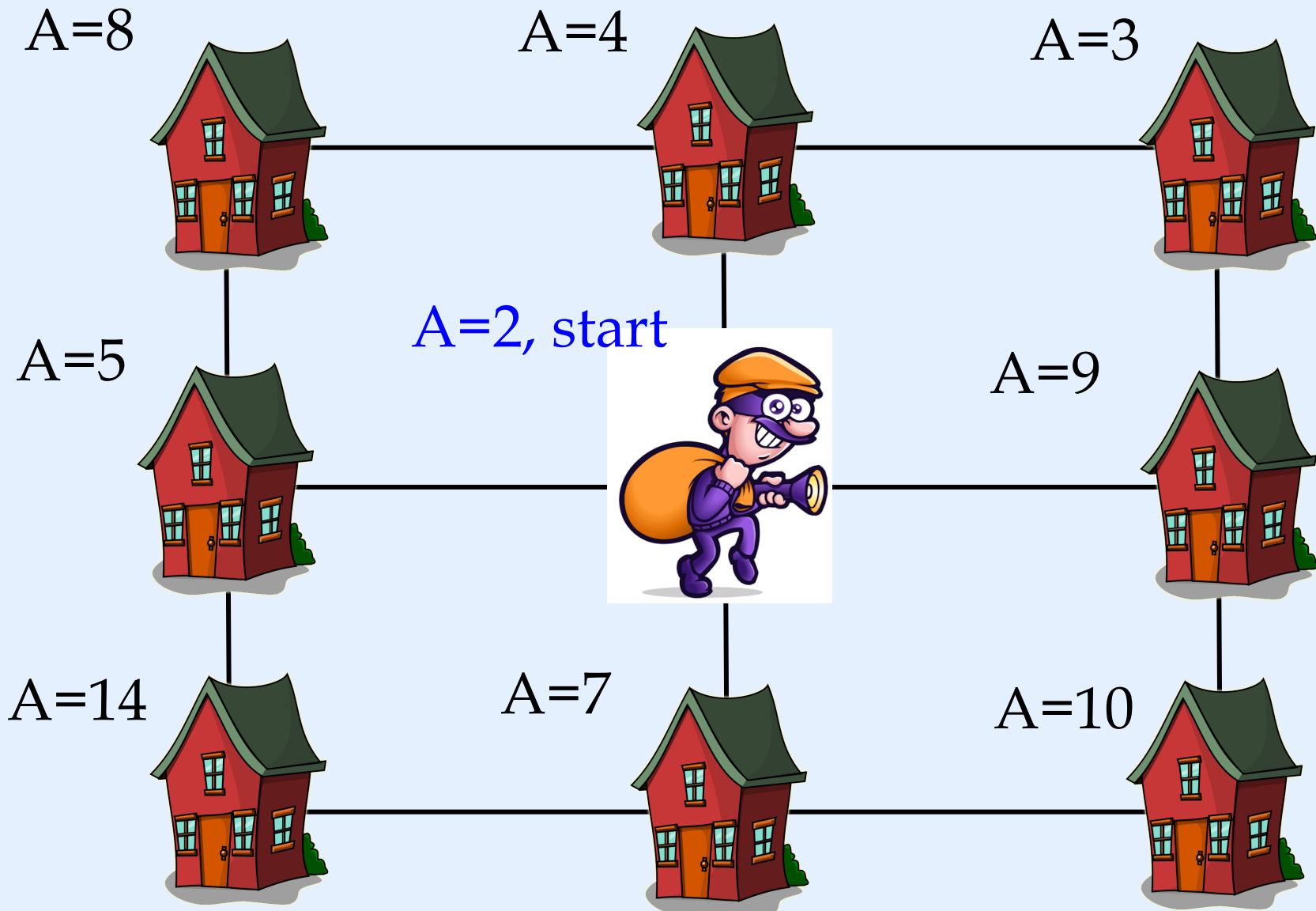
Ingredients

1. Residential burglary, crime of opportunity
2. Victimized once, easier to be victimized again
3. Introduce dynamically changing
“environmental” attractiveness $A(x,t)$

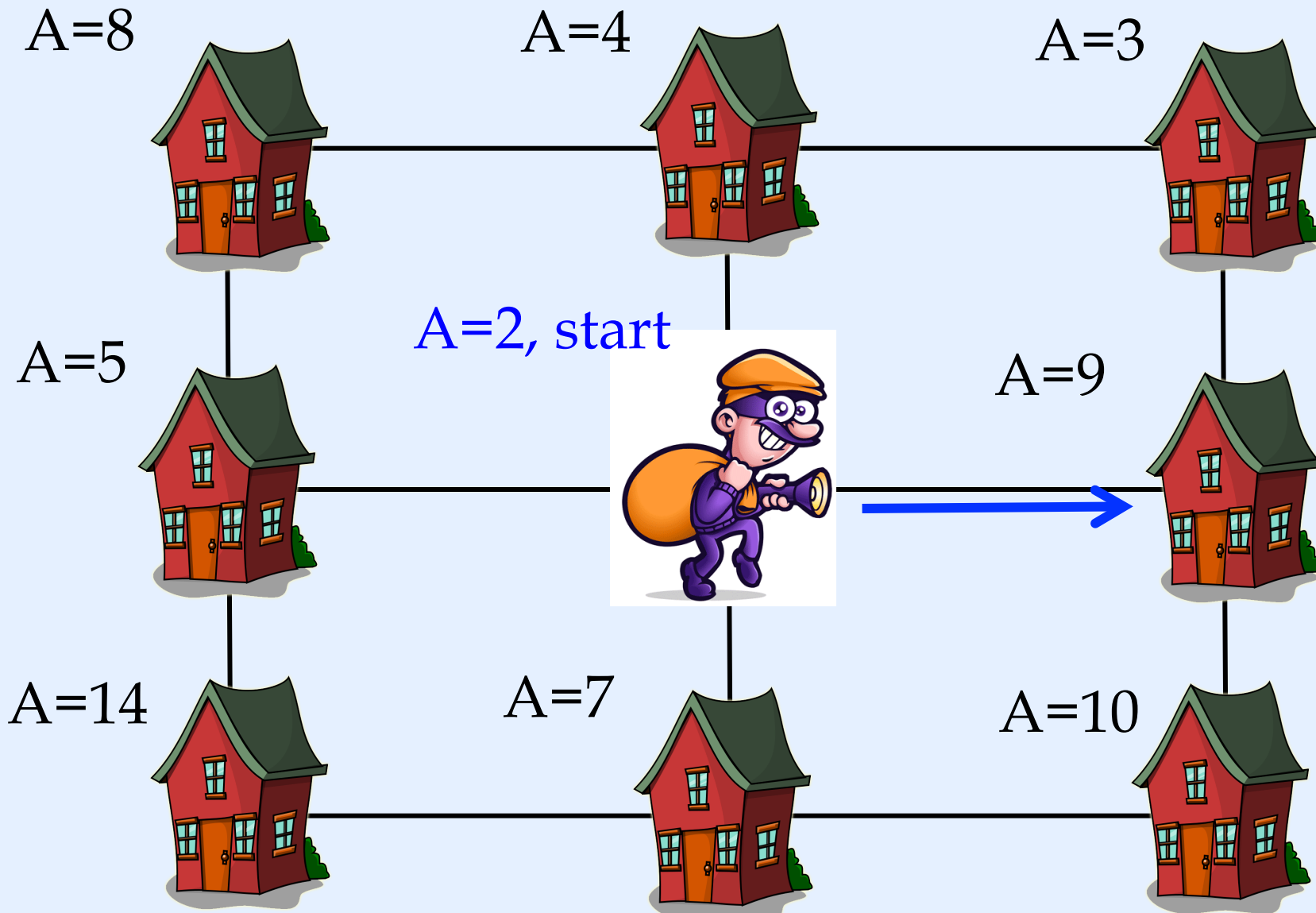
Sites are made “better” by criminal activity
Criminals are biased towards “better” sites

Feedback loops criminals/environment

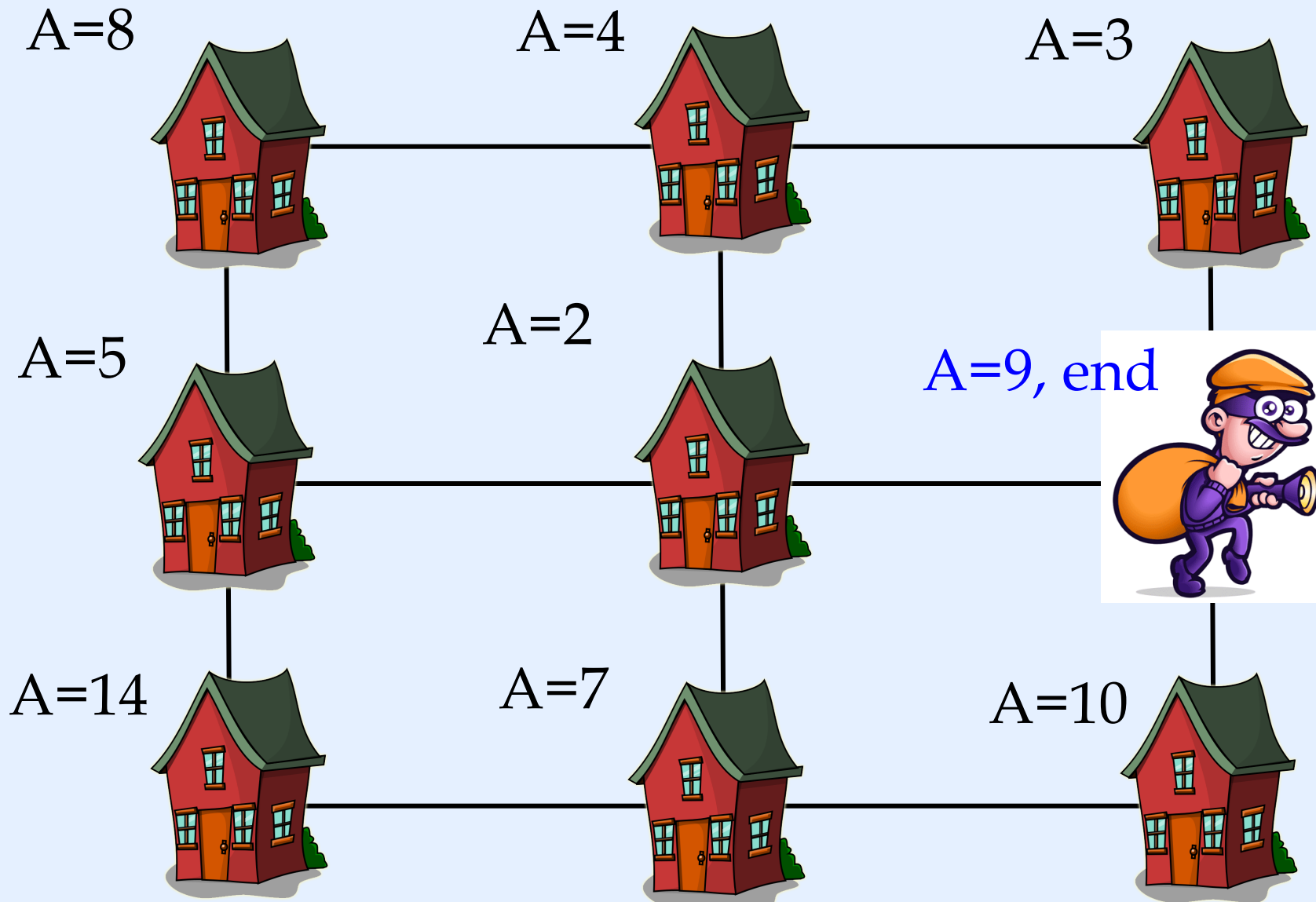
Agent based model, a cartoon



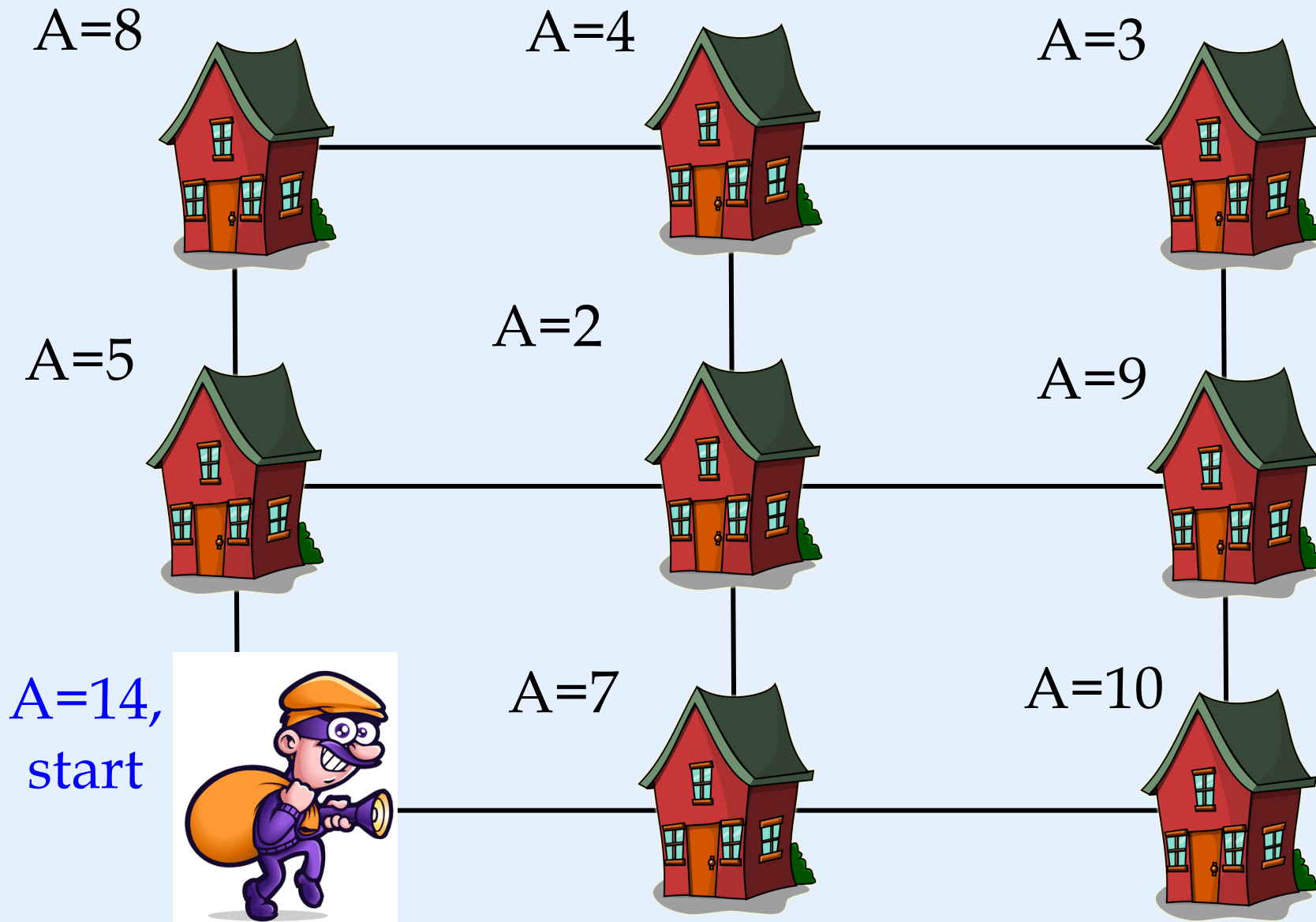
i) Site not very attractive, move



i) Site not very attractive, move



ii) Attractive site, steal



ii) Attractive site, steal

$A=8$



$A=4$



$A=3$



$A=5$



$A=2$



$A=9$



$A=14$,
steal,
leave



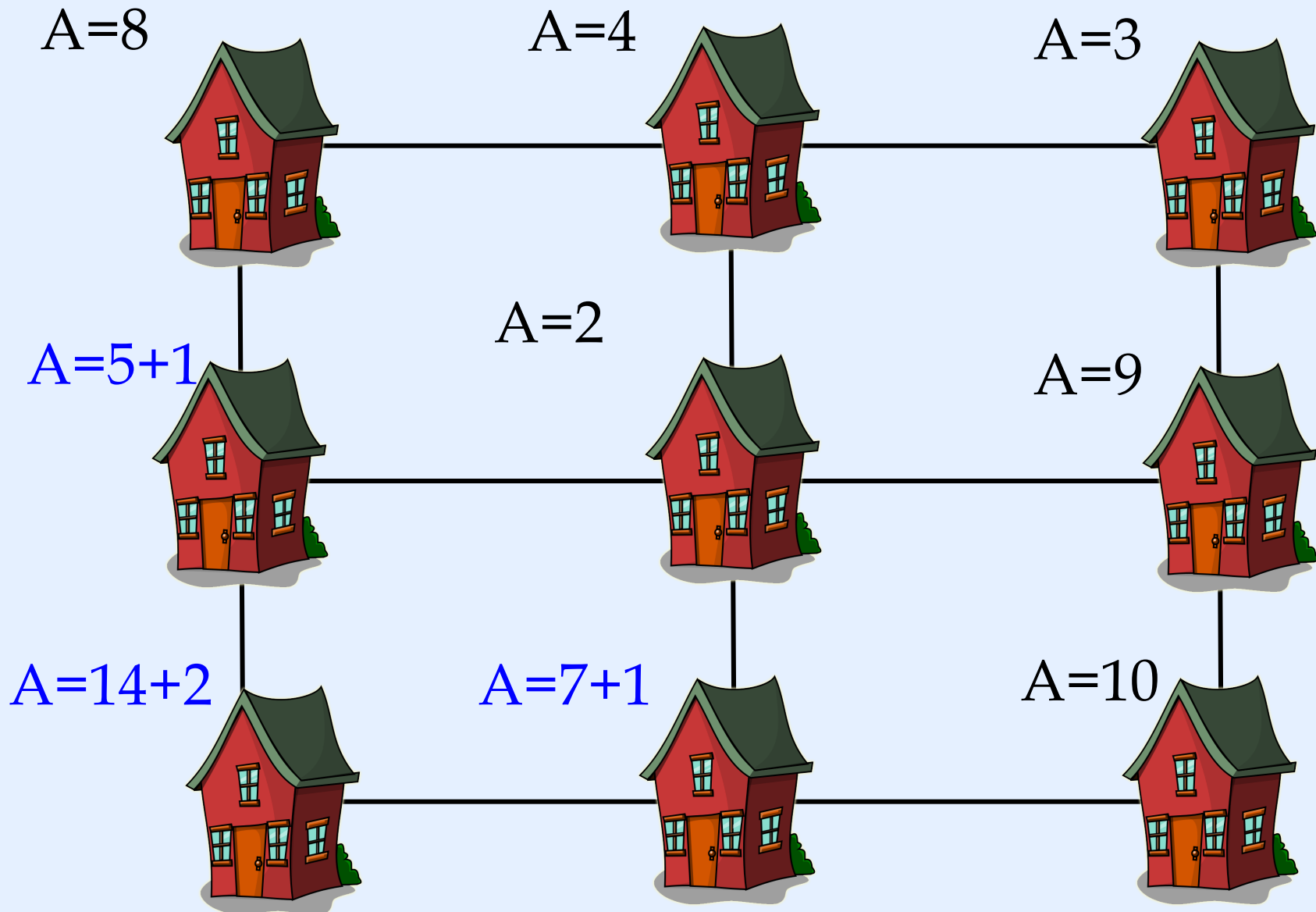
$A=7$



$A=10$



A increases close to theft site



A decreases away from theft site

$A=8-1$



$A=4-1$



$A=3-1$



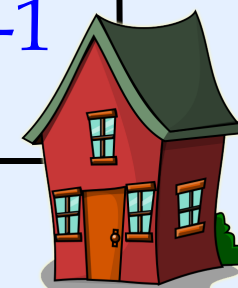
$A=6$



$A=2-1$



$A=9-1$



$A=16$



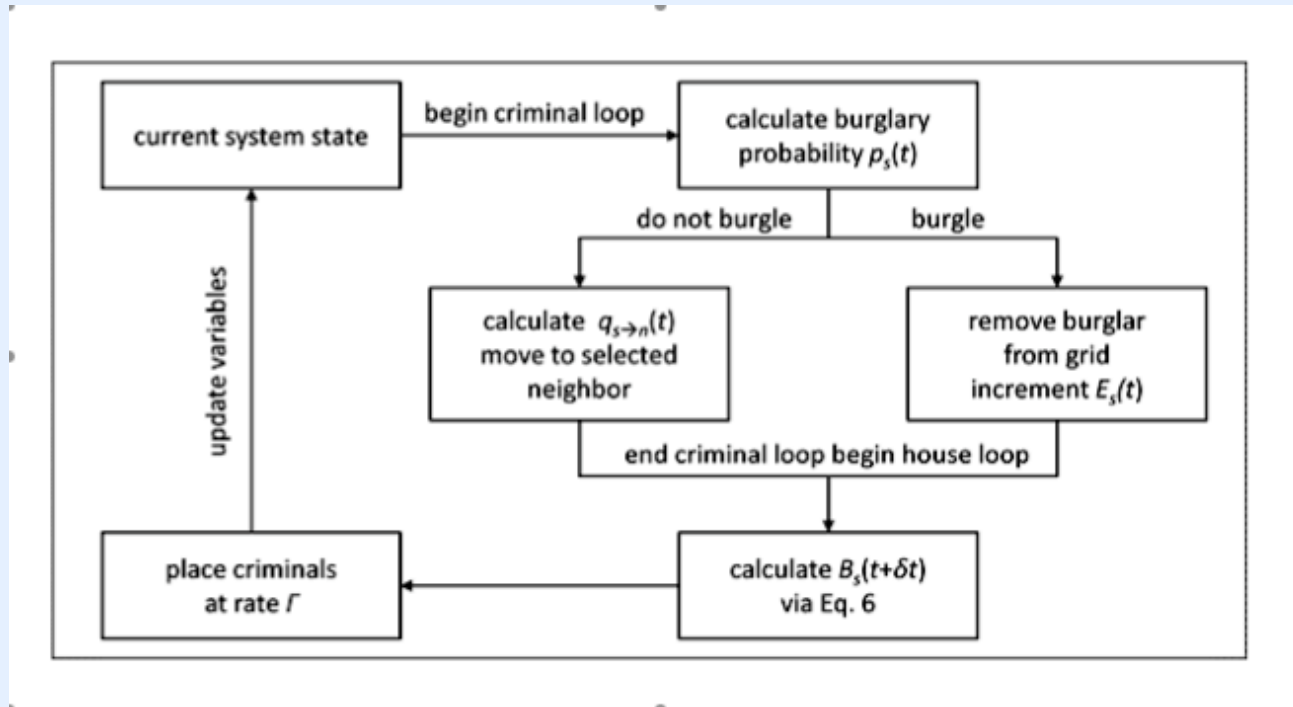
$A=8$



$A=10-1$

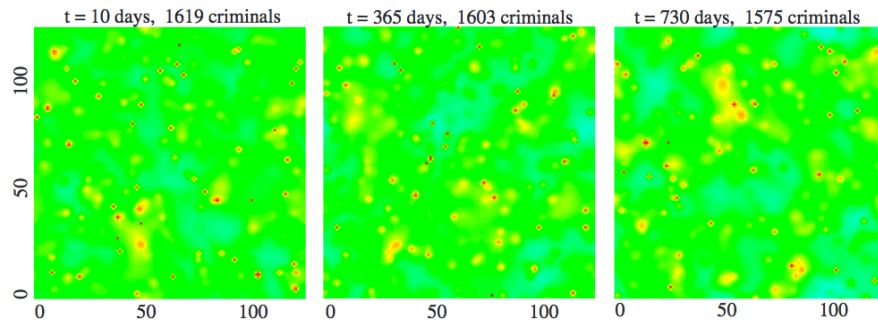


Scheme, parameters

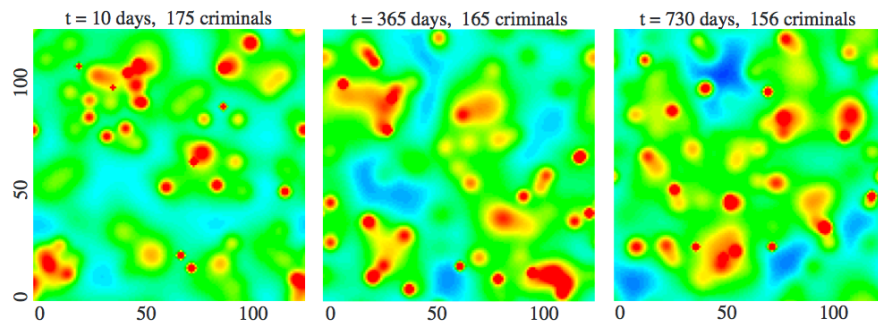


Parameter Name	Meaning
ℓ	Grid spacing
δt	Time step
ω	Dynamic attractiveness decay rate
η	Measures neighborhood effects (ranging from 0 to 1)
θ	Increase in attractiveness due to one burglary event
A_s^0	Intrinsic attractiveness of site s
Γ	Rate of burglar generation at each site

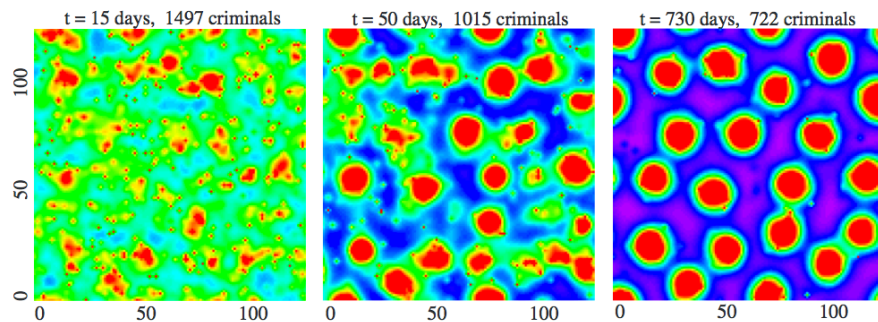
Simulations



(a)



(b)



(c)

Many criminals,
low increase in A
No hotspots

Few criminals,
large increase in A
Transient hotspots

Many criminals,
large increase in A
Stationary hotspots

Continuum model

$$\frac{\partial A}{\partial t} = \eta \nabla^2 A - (A - A_0) + \rho A$$

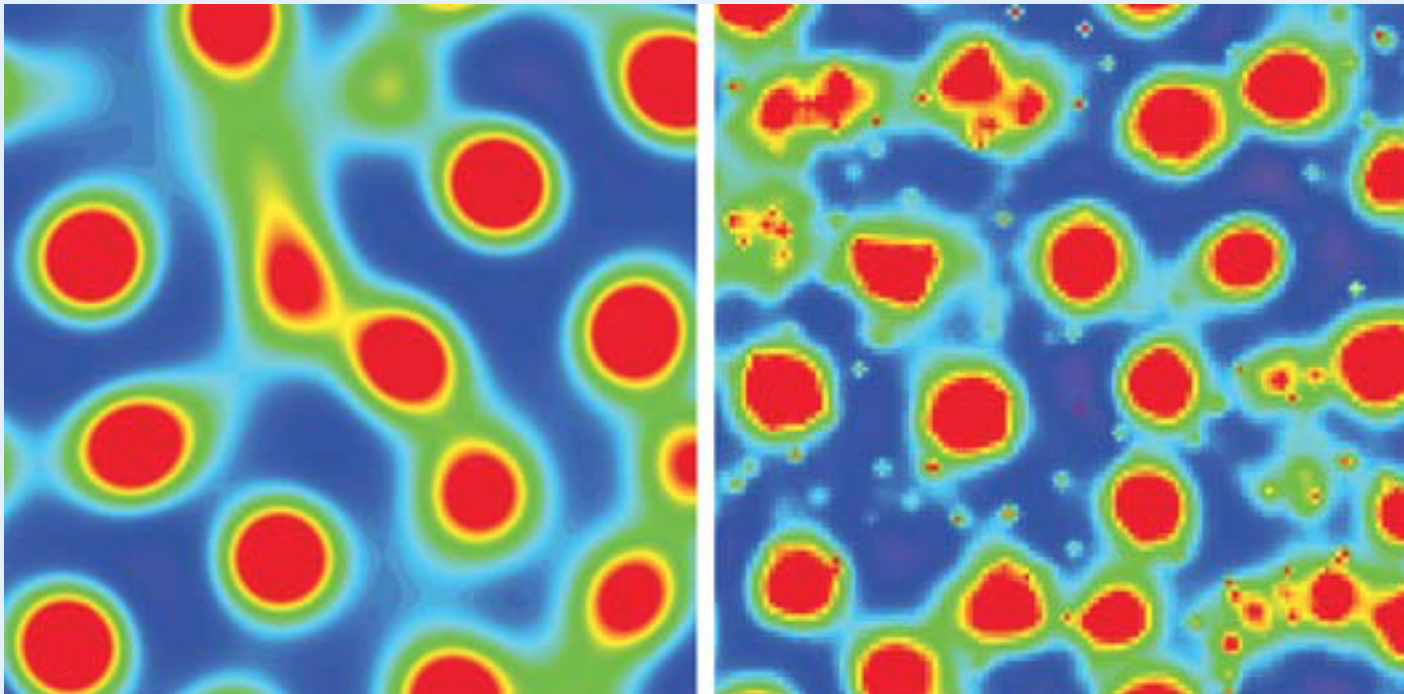
$$\frac{\partial \rho}{\partial t} = \vec{\nabla} \cdot \left[\vec{\nabla} \rho - \frac{2\rho}{A} \vec{\nabla} A \right] - \rho A + \Gamma$$

Attractiveness diffuses through environment
decay, replenished by criminal acts

Criminals depleted through reactions with system
spontaneously generated

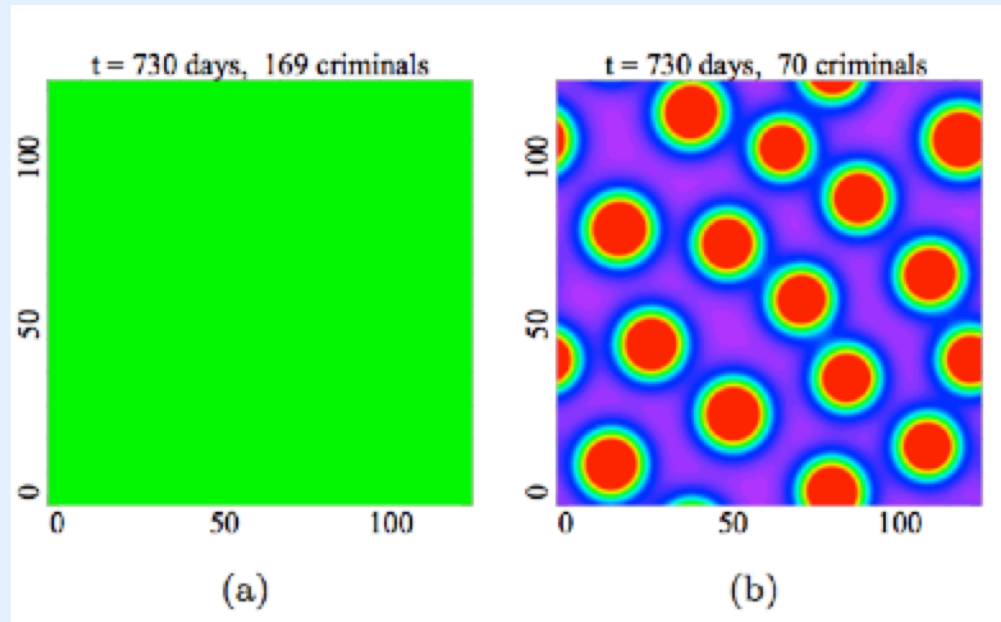
Diffusion and advective motion up gradients of A

Continuum vs. discrete



Steady state

Same parameters
as discrete (a), (b)



Same parameters
as discrete (c)

Many criminals,
large increase in A

Stationary hotspots: enhanced risk
of repeated crime is high enough to diffuse and be
sustained locally without binding distant crimes

Linear Stability Analysis

$$\frac{\partial A}{\partial t} = \eta \nabla^2 A - (A - A_0) + \rho A$$

$$\frac{\partial \rho}{\partial t} = \vec{\nabla} \cdot \left[\vec{\nabla} \rho - \frac{2\rho}{A} \vec{\nabla} A \right] - \rho A + \Gamma$$

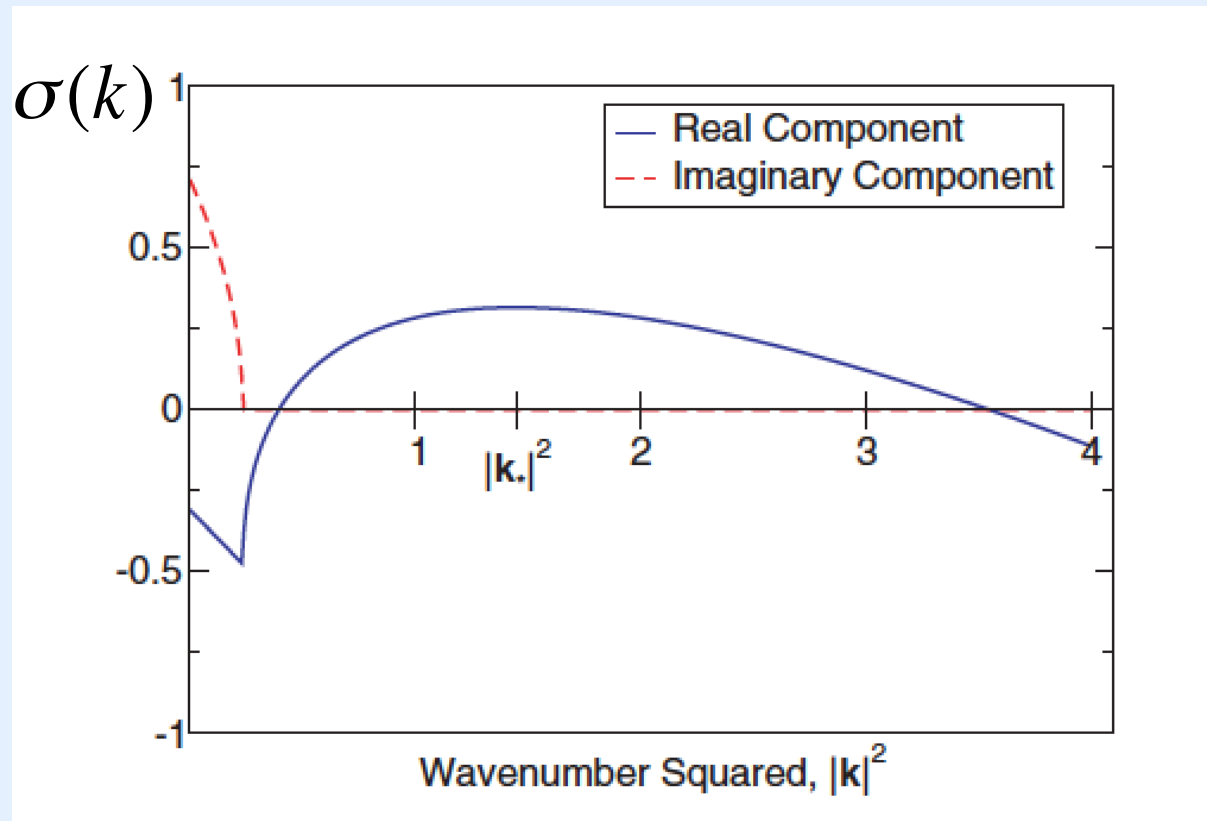
$$A^* = A_0 + \Gamma$$

$$\rho^* = \frac{\Gamma}{\Gamma + A_0}$$

$$A = A^* + \delta_A e^{\sigma t} e^{i\vec{k}\vec{x}}$$

$$\rho = \rho^* + \delta_\rho e^{\sigma t} e^{i\vec{k}\vec{x}}$$

Linear Stability Analysis

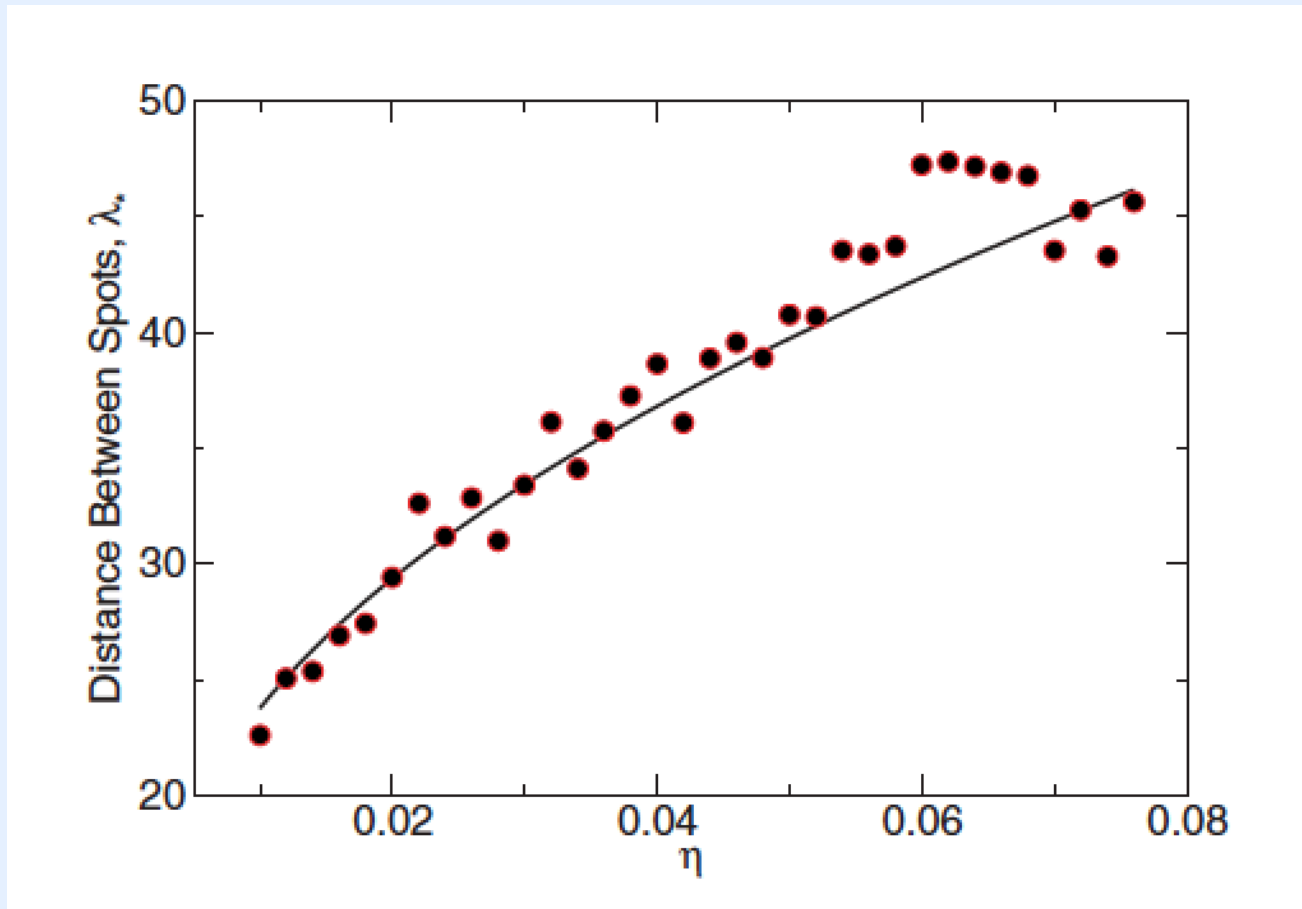


σ - imaginary

σ - real

Typical wavenumber k^* -- Typical distance $\lambda = 2\pi/k^*$

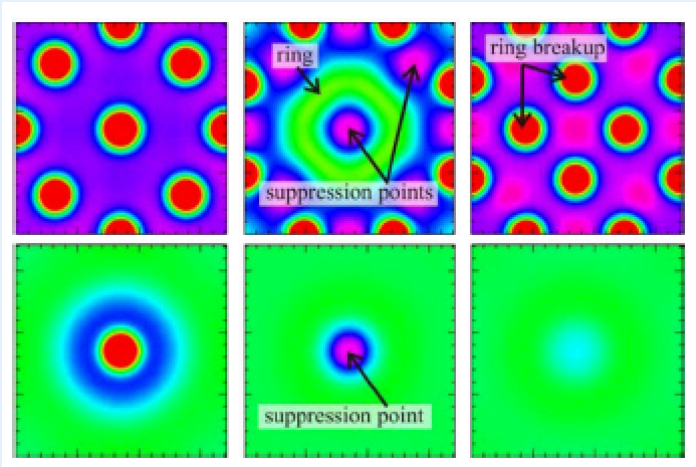
Hotspot separation



$\lambda = 2\pi/k^*$ -- fitted vs. simulated data

Larger diffusivity \rightarrow larger typical hotspot separation

Extensions



Suppression of hotspots

Policing

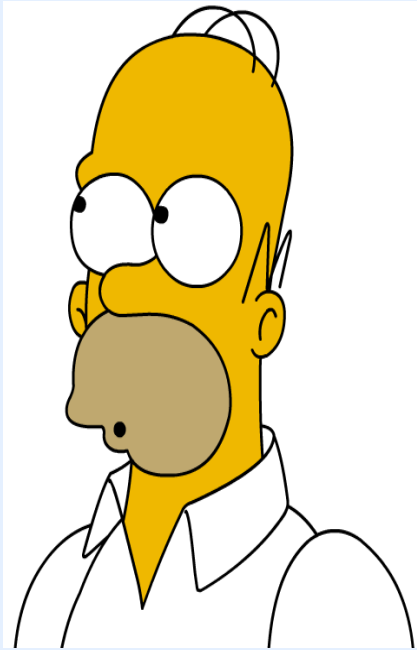
Spatial heterogeneity

Application to geographical data

Self exciting point processes

2. An informant and a criminal

The
apathetic



The villain



The
informant



The paladin



To commit a crime or not.
To collaborate or not.

Paladins: will not commit crime and will always report

Villains: will always commit crimes and never report

Apathetics: will not commit crimes but will not report

Informants: will commit crimes and will report

Assume constant population

$$P + V + A + I = N$$

strategies may change in time

The crime

Begin round - each player has value 1.

1. Choose a victimizer (V or I)
2. Choose a victim (any player)
3. A “crime” occurs with transfer of “wealth” $\delta < 1$

Victim \longrightarrow Victimizer
 $1 - \delta$ $1 + \delta$

4. Reporting?

If the victim is a **villain** or an **apathetic** no reporting
end of round - start over

If the victim is a **paladin** or an **informant** reporting
beginning of “investigation” - move to investigation



The investigation

Only if victim is **paladin** or **informant**.



1. “Witness” pool of m_P, m_I, m_A, m_V individuals
2. How many of them will corroborate victim’s story?

$$\omega = \frac{m_P + m_I}{m_P + m_I + m_A + m_V}$$

3. Victimizer is convicted with probability ω . The δ “loot” is returned to the victim. The victimizer is punished by θ .
4. Victimizer is free with probability $1-\omega$. The δ “loot” is kept by the victimizer. The victim gets extra loss ε due to retaliation.

Changing strategy

Find “loser” between victim and victimizer
(player with lower payoff)

Change his/her strategy by comparing
final payoffs and imitating

	Commits Crimes	No Crimes
Will Witness	<p>3 ↻</p> <p>1 ← 4</p> <p>Informants</p>	<p>2 ↻</p> <p>Paladins</p>
Will Not Witness	<p>1 ↑ 1</p> <p>1</p> <p>Villains</p> <p>3 ↻</p>	<p>2</p> <p>0</p> <p>Apathetics</p> <p>2 ↻</p>

Imitate victimizer - copy total strategy
Loser becomes an **informant** or a **villain**

OR

Imitate victim - become non criminal
copy only reporting strategy
Loser becomes a **paladin** or an **apathetic**

Bias removed, “empathy”

Agent based vs. continuum equations

$$\dot{P} = (I + V) \left[(P + I)^2 \frac{1}{2 - \theta} + I(A + V) \frac{1 - \delta - \epsilon}{2 - \epsilon} - P(A + V) \frac{1 + \delta}{2 - \epsilon} \right],$$

$$\dot{A} = (I + V) \left[V \frac{1 - \delta}{2} - A \frac{1 + \delta}{2} \right],$$

$$\dot{I} = I \left[(A + V) \frac{1 + \delta}{2} + P(A + V) \frac{1 + \delta}{2 - \epsilon} - (P + I)^2 \frac{1}{2 - \theta} - I(A + V) \frac{1 - \delta - \epsilon}{2 - \epsilon} - V(A + V) \right],$$

$$\dot{V} = V \left[(P + I)(A + V) \frac{1 + \delta}{2 - \epsilon} + (A - I) \frac{1 + \delta}{2} - (P + I)^2 \frac{1}{2 - \theta} - (I + V) \frac{1 - \delta}{2} \right],$$

At $t=0$ I_0, P_0, V_0, A_0

Study dynamics

Compare agent based (stochastic) and continuum descriptions

Find equilibria.

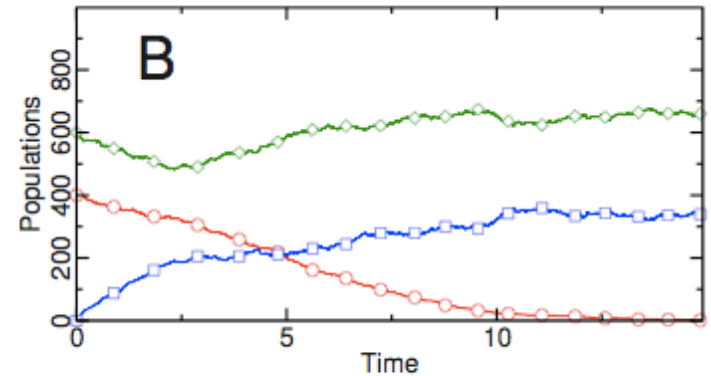
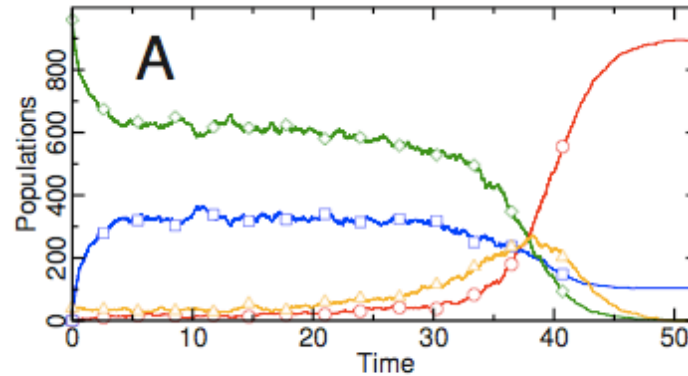
Stability?

Dynamics

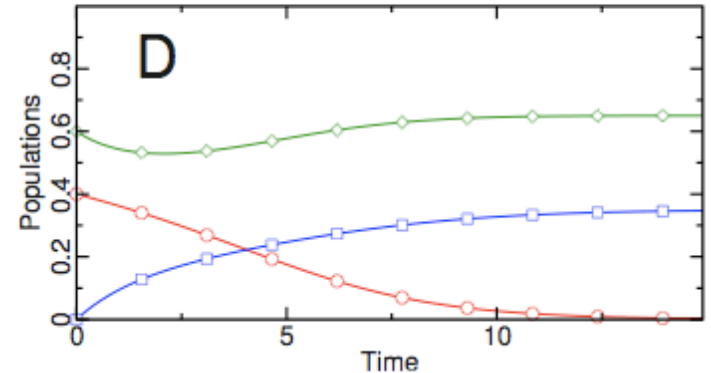
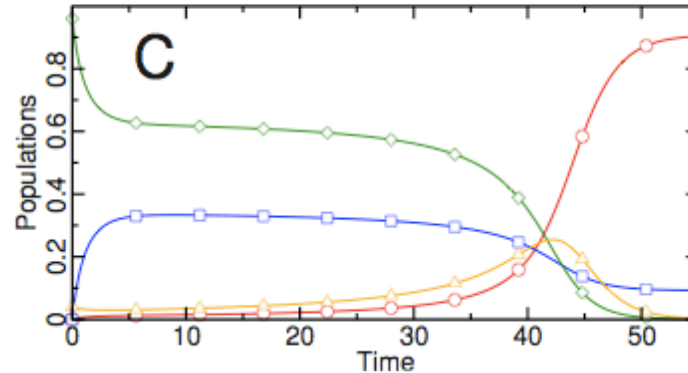
$$I_0=40, A_0=P_0=0, V_0=960$$

$$I_0=A_0=0, P_0=400, V_0=600$$

Stochastic



Deterministic



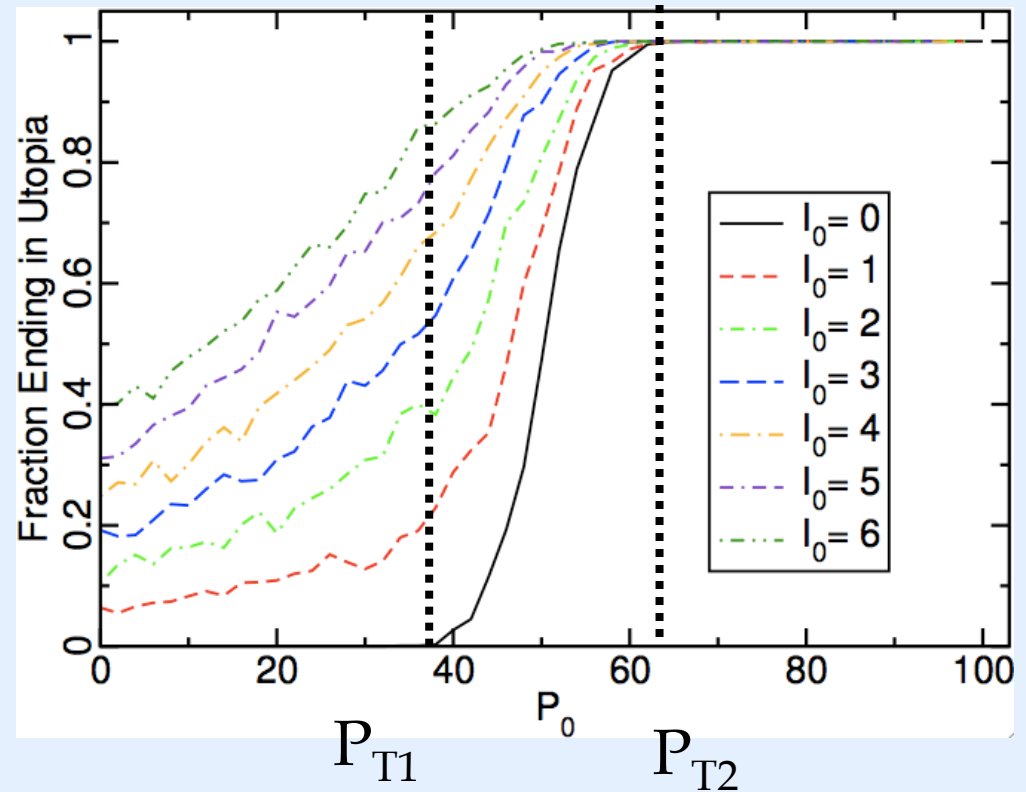
Paladins “win”
UTOPIA

Villains “win”
DYSTOPIA

$$\begin{aligned} \theta &= 0.6, \\ \varepsilon &= 0.2, \delta = 0.3 \\ N &= 1000 \end{aligned}$$

Upon closer inspection

$$N=100$$
$$A_0=0, V_0 = N - P_0 - I_0.$$



Achieving utopia is strongly dependent upon I_0 .

For $P_0 < P_{T2}$, adding one informant leads to 5-10% increases in the probability of reaching utopia

Linear Stability Analysis

From the deterministic case:

Dystopia is **unstable** to the addition of informants

A saddle point emerges

Utopia **stable** for $P > P_c$



Hence, if $I_0 > 0$

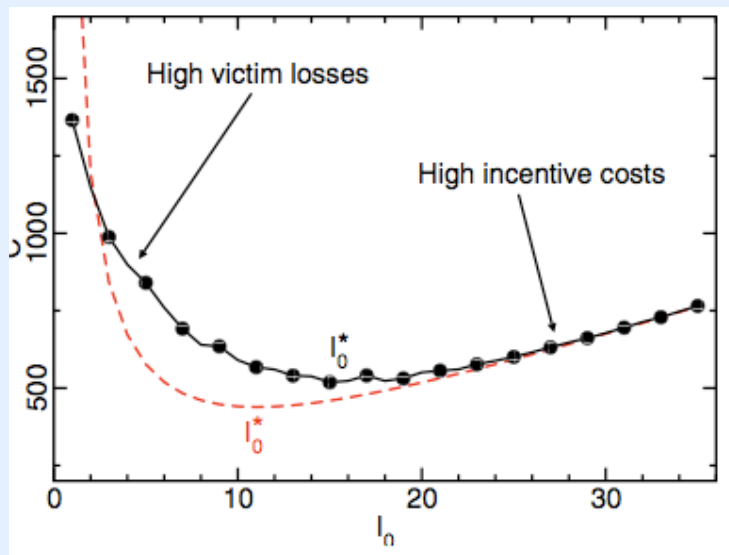
We always end up in utopia
according to the deterministic equations

Costs?

To achieve utopia we need informants
Let's recruit them from the villain pool.

This comes at a price.
at $t=0$ we convert I_0 villains

Cost = cost to convert informants + losses to society due to crime



Stochastic vs. **deterministic**

OPTIMAL CONVERSION

What do real people do?

Here is what UCI college kids do

Session	Initialization	Available Strategies	Session Variables			Strategies in last 5 rds.				End State
			Number of Subjects	Parameter Profile	Number of Periods	P	A	I	V	
1	90%V - 10%I	All	22	A	25	77%	1%	14%	8%	Utopia
2	90%V - 10%I	No A	24	A	25	66%	0%	21%	13%	Utopia
3	90%V - 10%P	No I	18	A	32	28%	17%	0%	56%	Dystopia
4	90%V - 10%I	All	18	B	30	64%	8%	17%	11%	Utopia
5	90%V - 10%P	No I	24	B	27	12%	16%	0%	73%	Dystopia

16 experiments, 10 treatments, ~ 400 students

Learning rounds, inertia, ‘parallelized’

Outcomes

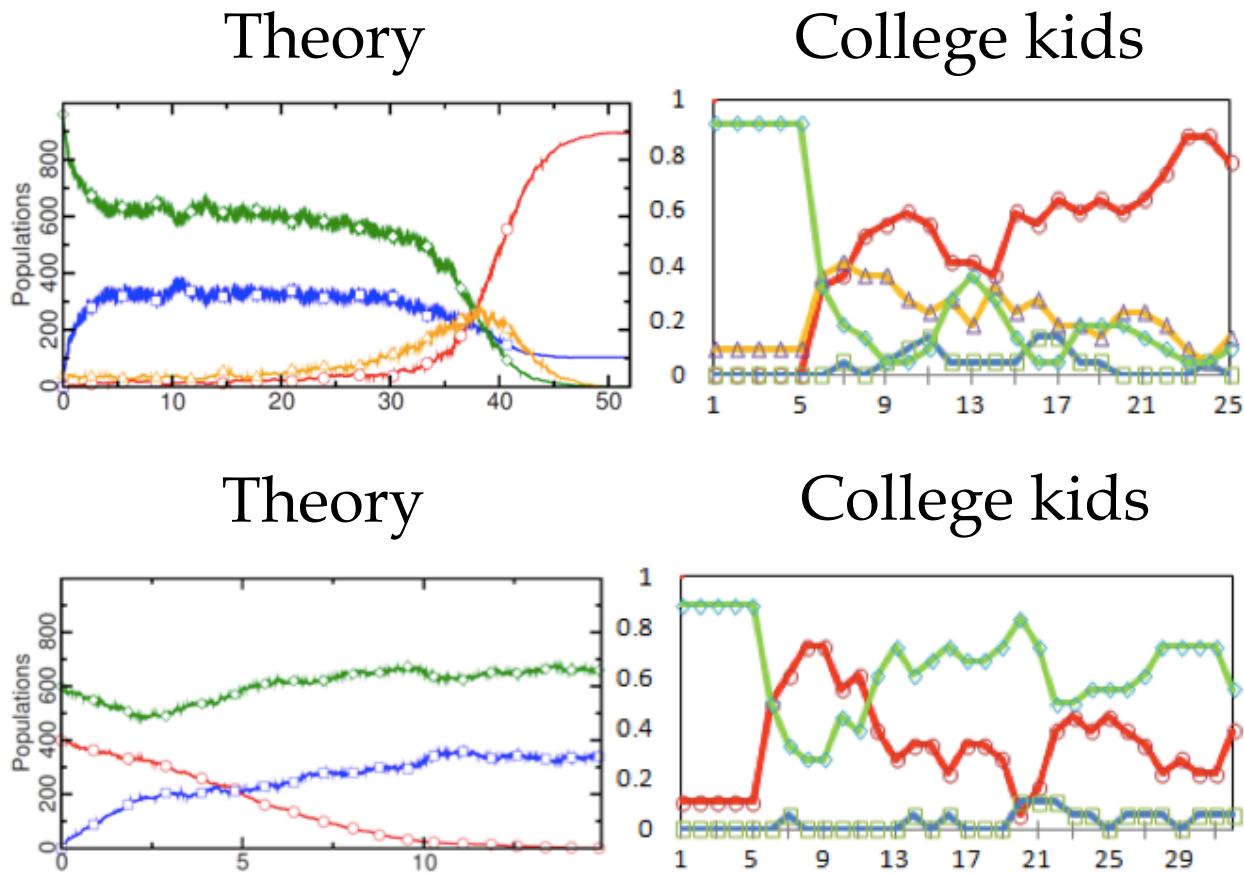


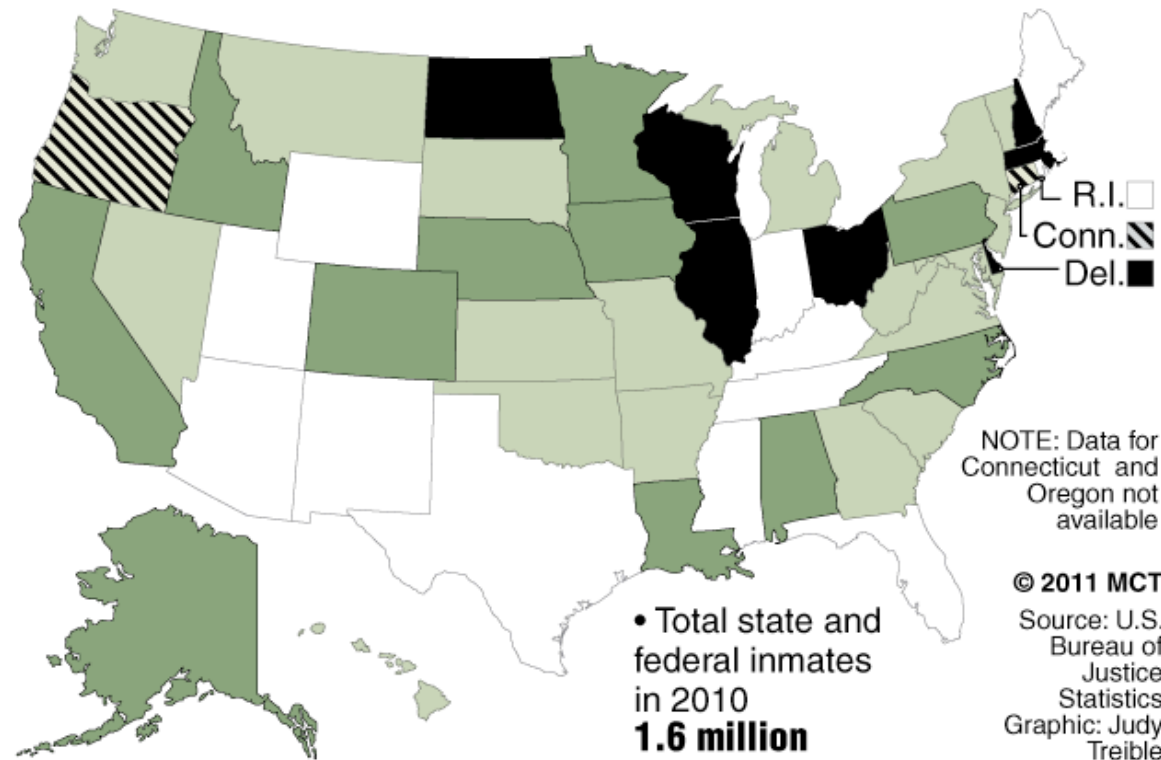
Fig 2. Evolution of Strategies. A and C depict the evolution of strategies from simulations using the imitation dynamic from (27) with with $N=1000$. B and D depict the evolution of strategies from our experiment Sessions 1 and 3. A and B allow all strategies; C and D do not allow the Informant strategy. In all figures, Paladins are red, Apathetics are blue, Informants are orange, and Villains are green.

3. Rehabilitation and Recidivism

Many U.S. prisons are full

State and federal prison population as a percent of highest prison capacity:

□ Less than 90% ■ 90-100% ■ 101-120% ■ 120% or more ▨ N/A



The carrot and the stick

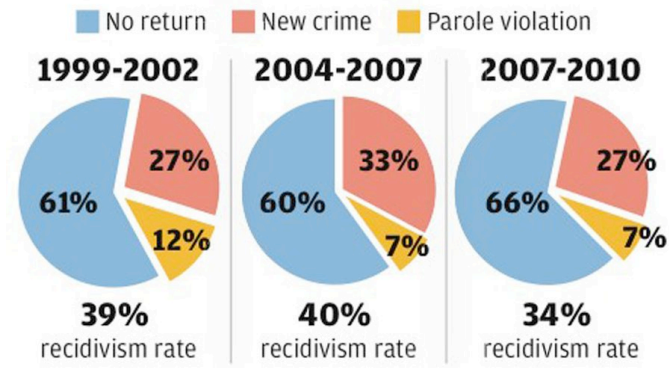
Report: Recidivism Rate Down as Texas Focuses on Treatment

Thanks partly to greatly expanded rehabilitation and treatment programs, Texas sent 11 percent fewer ex-convicts back to prison in recent years a significant drop in recidivism that is being replicated across the country, according to a new study.

BY MCCLATCHY NEWS | SEPTEMBER 25, 2012

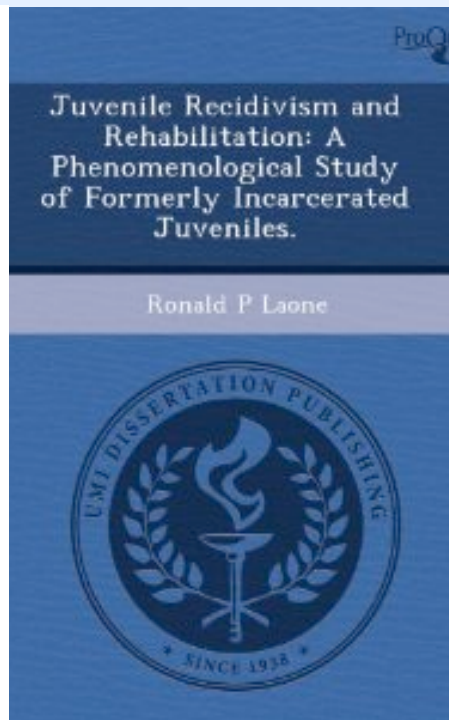
Recidivism declines in Ohio

A new study shows Ohio has had one of the nation's largest declines the number of parole violators who return to prison. State prison officials say they've been slower to revoke parole, allowing ex-convicts to remain in jobs and rehabilitative programs while safeguarding the public. Ohio's recidivism rate is at an 11-year low.



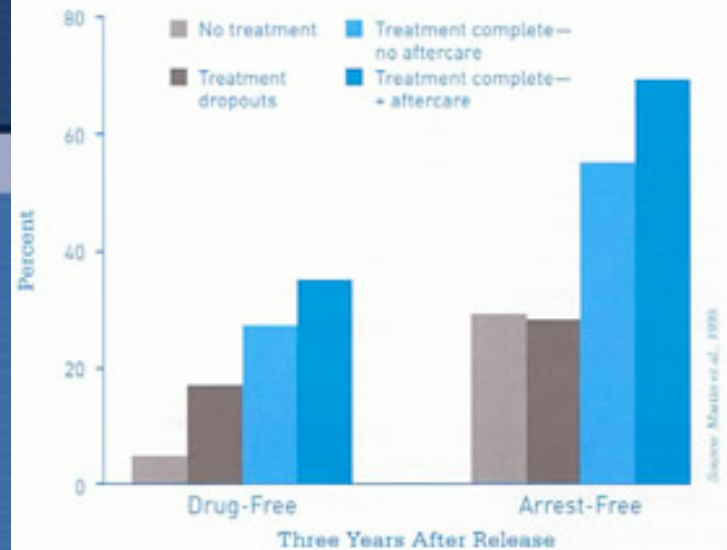
Source: Pew/ASCA Recidivism Survey

STAFF



Treatment in the criminal justice system reduces drug abuse and recidivism

Delaware Work Release Therapeutic Community + Aftercare



Source: Mottet et al., 1999

The criminal life

Players are exposed to criminal activities
and choose to commit crimes or not based on:

1. Past criminal history
2. Surrounding environment
3. If recidivists: enrollment in rehabilitation programs

Build and keep track of players criminal history

$N_0, N_1, N_2, \dots, N_k, \dots$

The criminal life

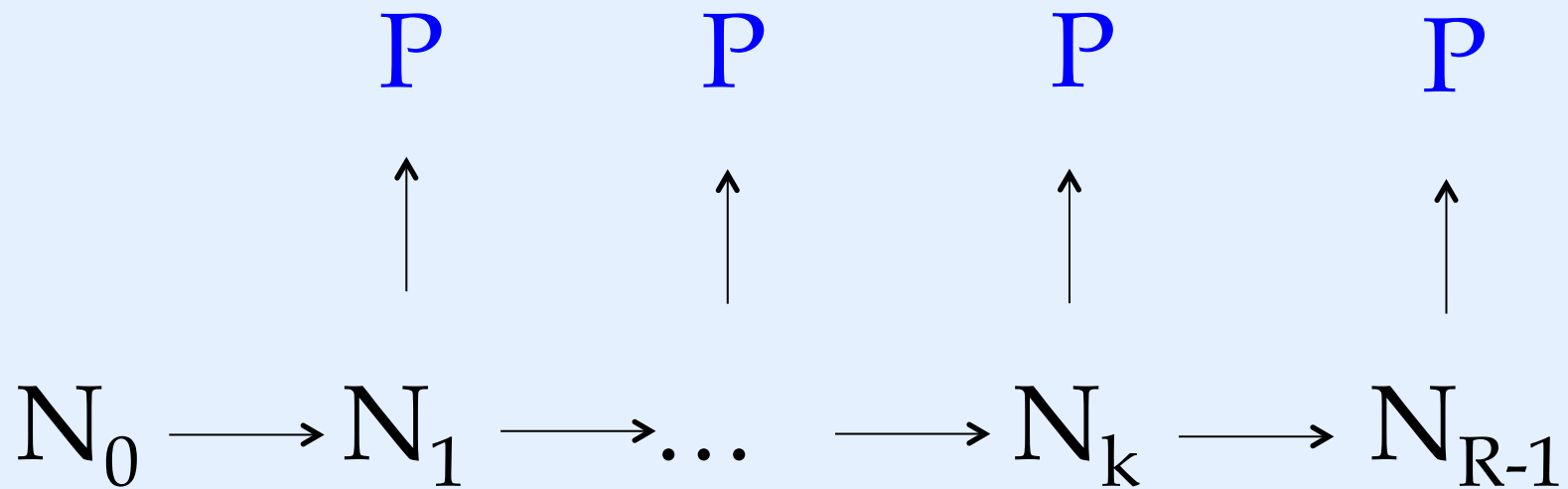
For each convicted crime: **PUNISH AND REHABILITATE**

Players may permanently reform: **PALADINS**

If the number of crimes reaches a threshold criminals are irreducible:
UNREFORMABLES



Paladins and Unreformables



At the end of our irreversible game players
in one of two sinks:

Paladins P
Unreformables U

Define natural "order parameter" P/U

Decisions – Committing crimes?

For each individual i

$$\begin{array}{l} k_u \text{ unpunished crimes} \quad k_p \text{ punished crimes} \\ k \text{ total} = k_u + k_p \end{array}$$

Personal history - p_i

Societal input - s_i

Attenuation due to rehabilitation - a_i

$$P_{Crime} = \left(\frac{p_i + s_i}{2} \right) a_i$$

Mathematical choices

$$p_i = \frac{p_0 + k_u}{k_u + p_0 + \theta k_p}$$

$$s_i = \frac{\sum_{k \neq 0} N_k + U}{N}$$

$$a_i = (1 - h e^{-t/\tau})$$

θ punishment
unpunished crimes - k_u
punished crimes - k_p

Crime generates more crime

h incentives
 τ time duration

$$P_{Crime} = \left(\frac{p_i + s_i}{2} \right) a_i \longrightarrow$$

After crime:
punish with probability $\alpha = 1/4$

After the crime

If no crime committed : reform with probability

$$P_{reform} = \frac{\alpha P}{N}$$

If a crime committed

if not arrested/punished
don't reform

$$P_{reform} = 0$$

if arrested/punished
reform with probability

$$P_{reform} = \frac{1}{2} \left(\frac{\alpha P}{N} + \frac{\theta k_p}{k_u + p_0 + \theta k_p} \right)$$

Variables/Parameters

P	paladins
U	unreformables (who have have been punished R times)
N_0	neutral citizens that have committed no crimes
N_k	citizens that have committed $k = k_u + k_p$ crimes
k_u	number of unpunished crimes
k_p	number of punished crimes
h	parameter quantifying resources
τ	duration of intervention
θ	severity of punishment
p_0	punishment amplitude parameter
α	arrest and conviction probability
R	maximum number of punished crimes

Irreversible system, very sensitive to initial conditions

Runs

400 individuals, 25 replicas

$\tau=2$ $p_0=0.1$ $\alpha=1/4$ $R=3$

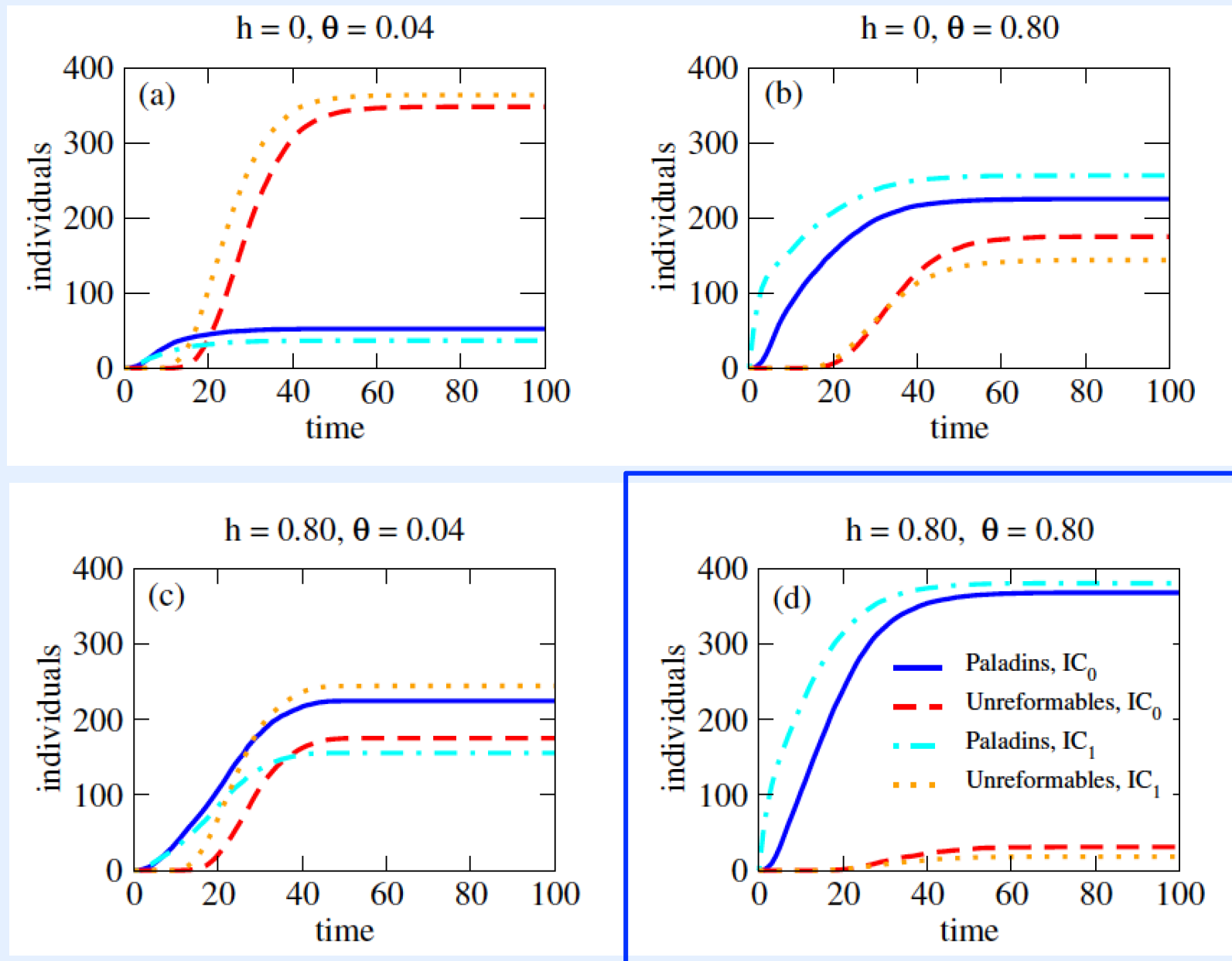
vary h, θ

IC0 : 400 in N_0 at time $t=0$

IC1: 200 in N_0 , 200 in N_1 at time $t=0$

Parallel updates

Results



Total resources are finite!

Carrot, stick or both?



The **carrot**:
Rehabilitation resources $h\tau$

The **stick**:
Punishment resources θ

Increase one,
Decrease the other

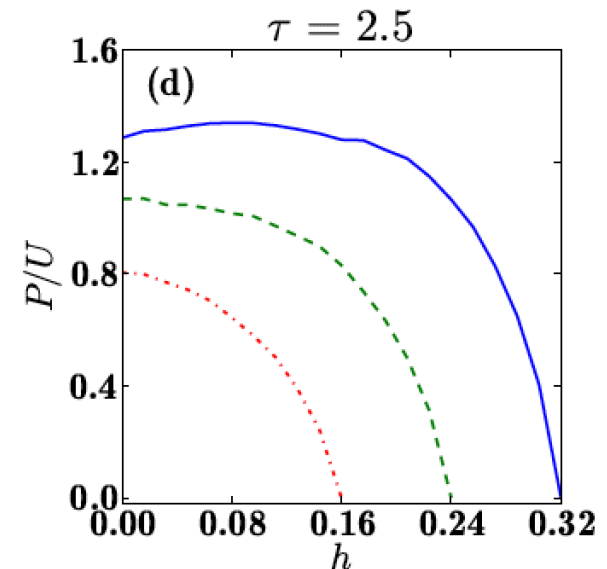
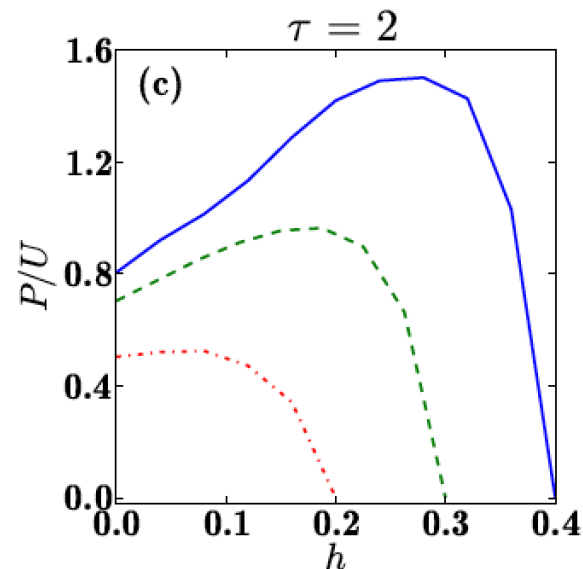
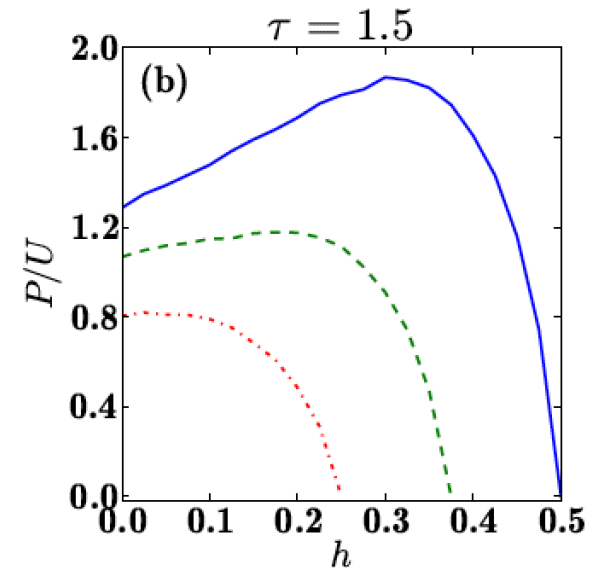
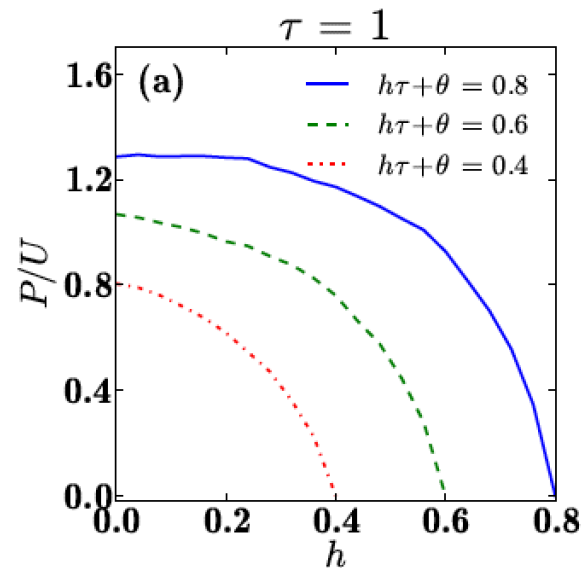
$$h\tau + \theta = \text{const}$$

P/U with finite resources

—————
 $h\tau + \theta = 0.8$

- - - - -
 $h\tau + \theta = 0.6$

.....
 $h\tau + \theta = 0.4$



P/U with finite resources

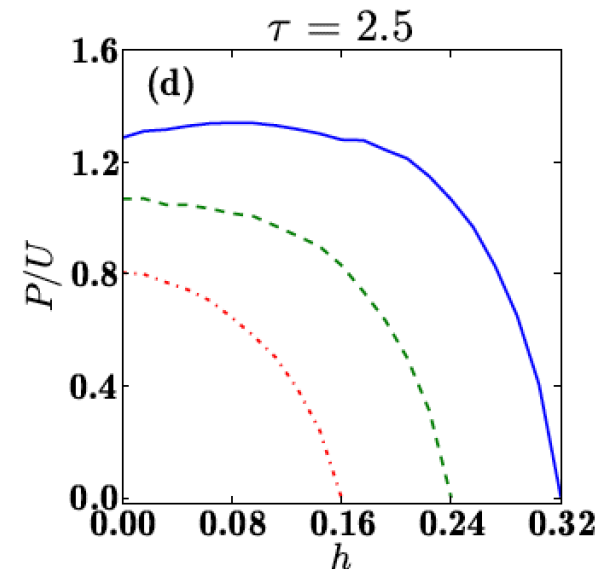
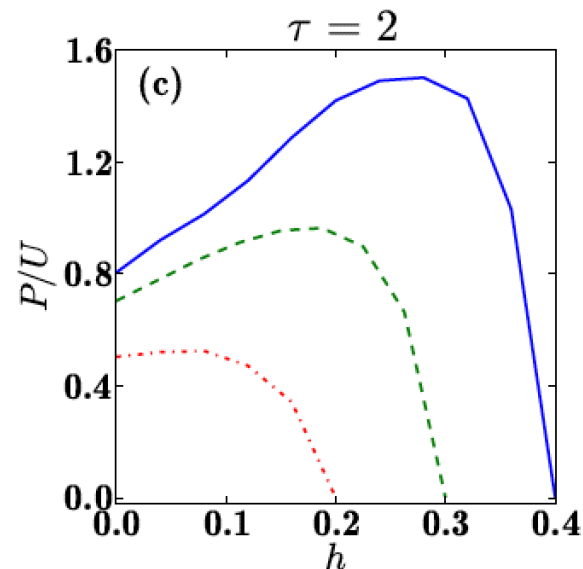
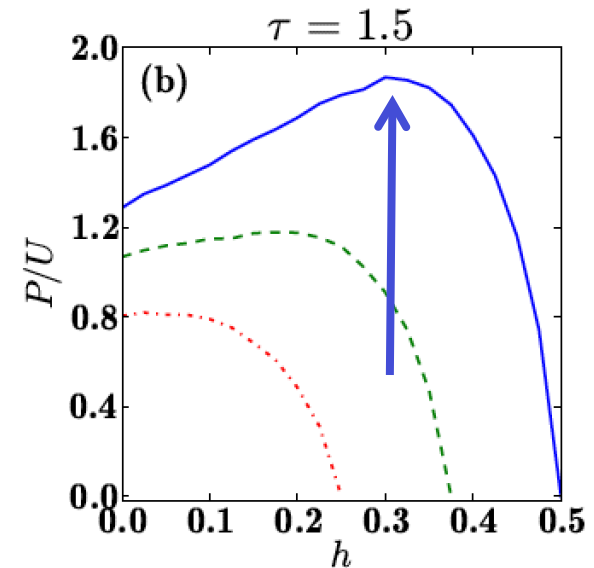
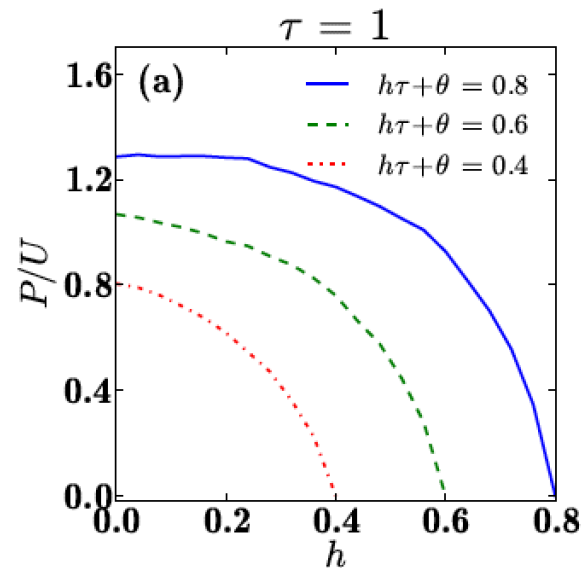
$$h\tau + \theta = 0.8$$

Optimal
parameter
set

$$h = 0.30$$

$$\tau = 1.5$$

$$\theta = 0.35$$



Best strategy

Enough stick

Enough carrots
For enough time

Too lenient or too harsh punishments are not as effective as judicious balancing of the two

ODEs

Challenges:

Memory effects

Open ended

Parallel vs. Sequential updates

Keep track of indices k_u, k_p

$$N_k \rightarrow N_{k_u, k_p}$$

$$P_{\text{crime}} \rightarrow c_{k_u, k_p}$$

$$P_{\text{reform}} \rightarrow r_{k_u, k_p}$$

Agent based vs. continuum equations

$$\dot{N}_{0,0} = - \left[c_{0,0} + (1 - c_{0,0}) \frac{\alpha P}{N} \right] N_{0,0},$$

$$\dot{N}_{0,k_p} = - \left[c_{0,k_p} + (1 - c_{0,k_p}) \frac{\alpha P}{N} \right] N_{0,k_p} + \alpha c_{0,k_p-1} (1 - r_{0,k_p}) N_{0,k_p-1},$$

for $k_p = 1, \dots, R - 1$

$$\dot{N}_{k_u,0} = - \left[c_{k_u,0} + (1 - c_{k_u,0}) \frac{\alpha P}{N} \right] N_{k_u,0} + c_{k_u-1,0} (1 - \alpha) N_{k_u-1,0},$$

for $k_u \geq 1$

$$\dot{N}_{k_u,k_p} = - \left[c_{k_u,k_p} + (1 - c_{k_u,k_p}) \frac{\alpha P}{N} \right] N_{k_u,k_p} + c_{k_u-1,k_p} (1 - \alpha) N_{k_u-1,k_p}$$
$$+ \alpha c_{k_u,k_p-1} (1 - r_{k_u,k_p}) N_{k_u,k_p-1},$$

for $k_u \geq 1$ and $1 \leq k_p \leq R - 1$

ODEs

$$\dot{P} = \sum_{k_u=0}^{\infty} \sum_{k_p=0}^{R-1} \left[(1 - c_{k_u, k_p}) \frac{\alpha P}{N} \right] N_{k_u, k_p} + \alpha \sum_{k_u=0}^{\infty} \sum_{k_p=0}^{R-2} c_{k_u, k_p} r_{k_u, k_p+1} N_{k_u, k_p},$$

$$\dot{U} = \alpha \sum_{k_u=0}^{\infty} c_{k_u, R-1} N_{k_u, R-1},$$

$$c_{k_u, k_p}(t) = \frac{1}{2} \left[\frac{p_0 + k_u}{p_0 + k_u + \theta k_p} + \frac{\sum_{\{k_u, k_p \neq 0, 0\}} N_{k_u, k_p}}{N} \right] \left(1 - h e^{-(t-t_{last})/\tau'} \right)$$

$$r_{k_u, k_p}(t) = \frac{1}{2} \left[\frac{h\alpha P}{N} + \frac{\theta k_p}{\theta k_p + k_u + p_0} \right]. \quad t - t_{last} = t / k_p$$

Conservation of population

$$\sum_{k_u=0}^{\infty} \sum_{k_p=0}^{R-1} \dot{N}_{k_u, k_p} + \dot{P} + \dot{U} = 0,$$

Truncate

$$\dot{N}_{\text{uncatch}} = (1 - \alpha) \sum_{k_p=0}^{R-1} c_{k_u^*, k_p} N_{k_u^*, k_p}.$$

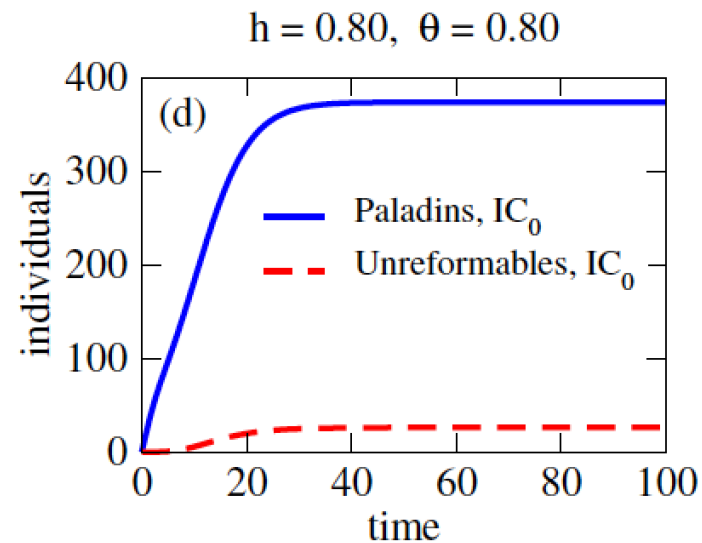
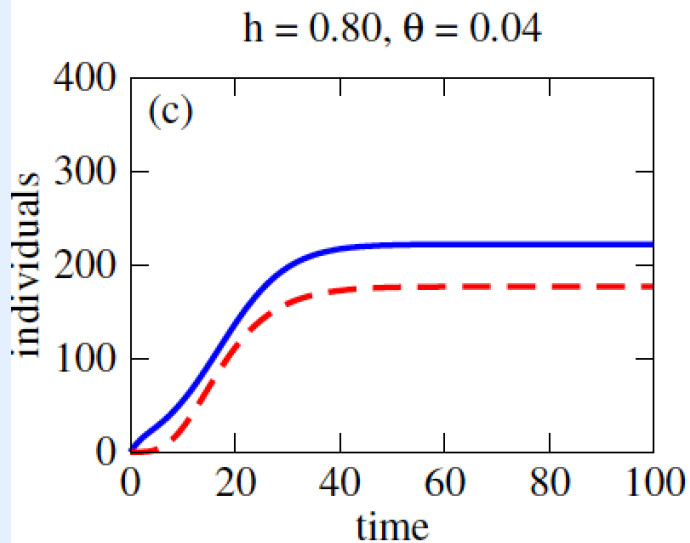
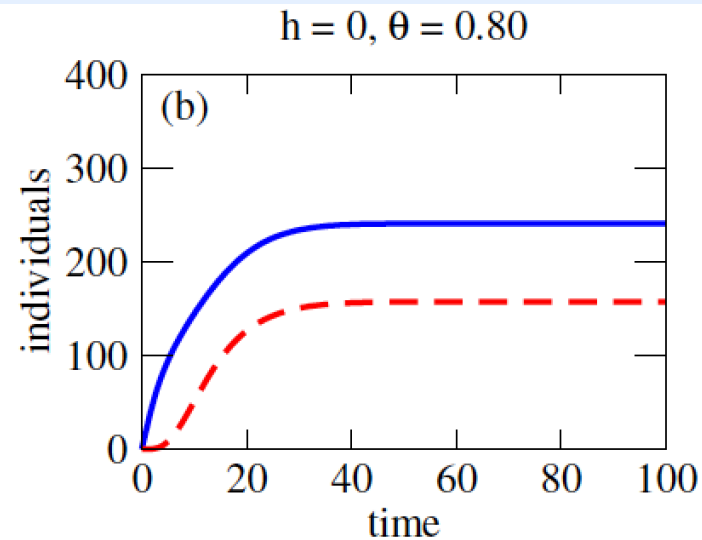
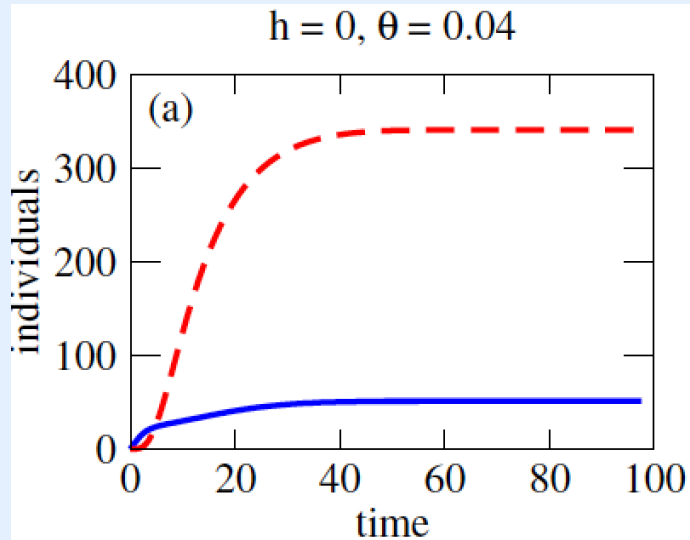
Relevant parameters

h resources for rehabilitation

τ time for rehabilitation

ϑ punishment

A qualitative match, IC0



4. Criminal Networks

Organized crime: complex hierarchical structures

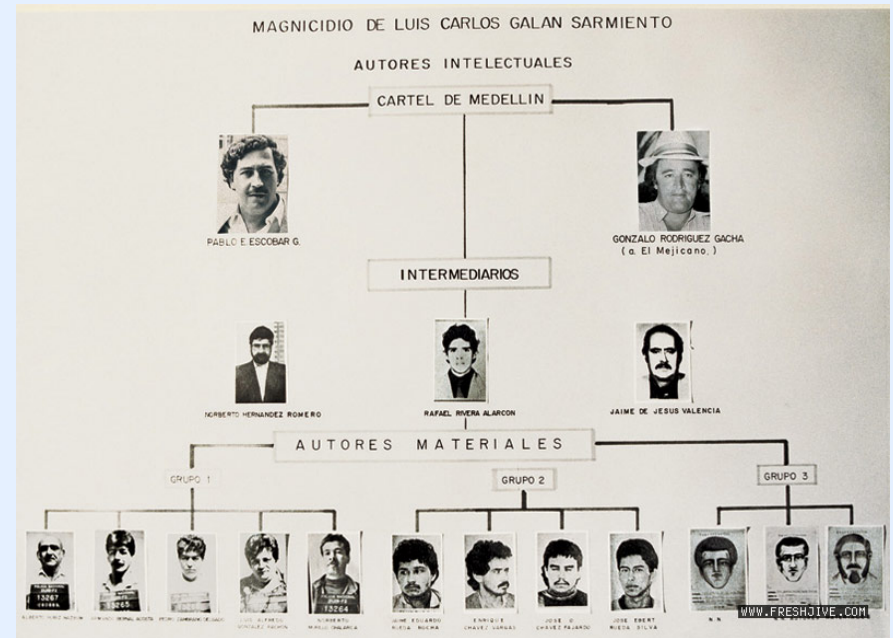
3 - I MANDAMENTI DI COSA NOSTRA



Pablo Escobar (Medellin) El Chapo (Sinaloa)
The Godfather (Cosa Nostra)



Medellin, Colombia



CIFUENTES VILLA Drug Trafficking Organization

Foreign Narcotics Kingpin Designation Act (Kingpin Act) February 2011

Jorge Milton CIFUENTES VILLA (a.k.a. Elkin de Jesus LOPEZ SALAZAR) DOB 13 May 1965; POB Medellin, Colombia. CC 7548733 (Colombia). Passport AL720622 (Colombia). CURP CIV265951HINEFLR06 (Mexico). Indicted on Drug Trafficking & Money Laundering Charges Southern District of Florida (November 2010).

Joaquin GUZMAN LOERA (a.k.a. "El Chapo") DOB 25 Dec 1954; POB Mexico. Leader of the SINALOA CARTEL. Previously Identified by the President as a Significant Foreign Narcotics Trafficker. Reward for Information Leading to the Arrest and Conviction of GUZMAN LOERA: \$5,000,000.00 USD. 1-866-294-0820

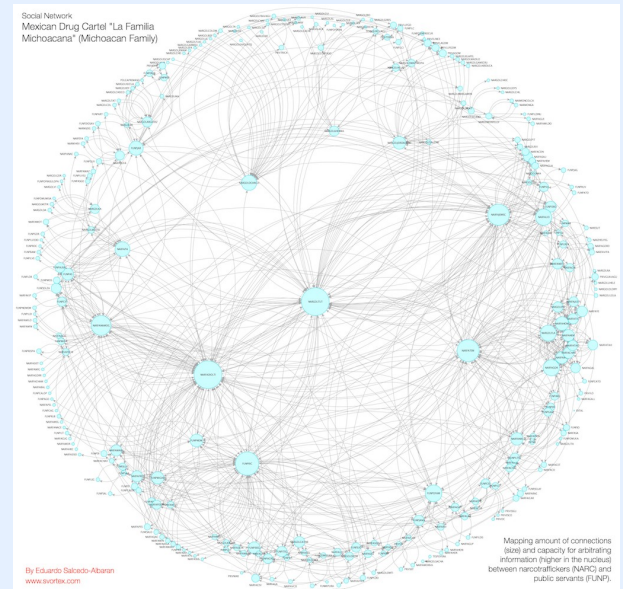
Individuals Assisting the Organization's Drug Trafficking Activities

Luis Ines CIFUENTES VILLA DOB 4 Nov 1956 CC 3222460 (Colombia)	Jaime Alberto ROLL CIFUENTES DOB 15 Mar 1979 CC 8966728 (Colombia)	Dolly de Jesus CIFUENTES VILLA DOB 14 Jun 1964 CC 4302013 (Colombia)	Carlene VILLA DE CIFUENTES DOB 30 Aug 1944 CC 2126247 (Colombia)	Elidabrada Alexander CIFUENTES VILLA DOB 18 Jan 1968 CC 7162561 (Colombia)	Alfredo ALVAREZ ZEPEDA a.k.a. Gabino ONTIVEROS RIOS DOB 12 Sep 1977 POB Culiacan, Sinaloa, Mexico	Mario Tullio FLORES SEPULVEDA DOB 8 Apr 1962 CC 7039929 (Colombia)
Shirley Yelin YELINER DOB 23 Jan 1961 CC E-8- 92586 (Panama)	Fabian Rodrigo GALLEGOS MARTIN DOB 25 Aug 1967 CC 9522292 (Colombia)	Milton Geovany MARTINEZ GOMEZ DOB 1 Jul 1972 CC 11186154 (Colombia)	Winston NICHOLLS EASTMAN DOB 27 Mar 1943 CC 2199771 (Colombia)	Jose Luis GOMEZ POZUECOS DOB 25 May 1941 Passport BC046529 (Spain)	David GOMEZ ORTIZ DOB 14 Aug 1977 CC 9339142 (Colombia)	

Individuals Directed by or Acting for or on Behalf of Jorge Milton CIFUENTES VILLA

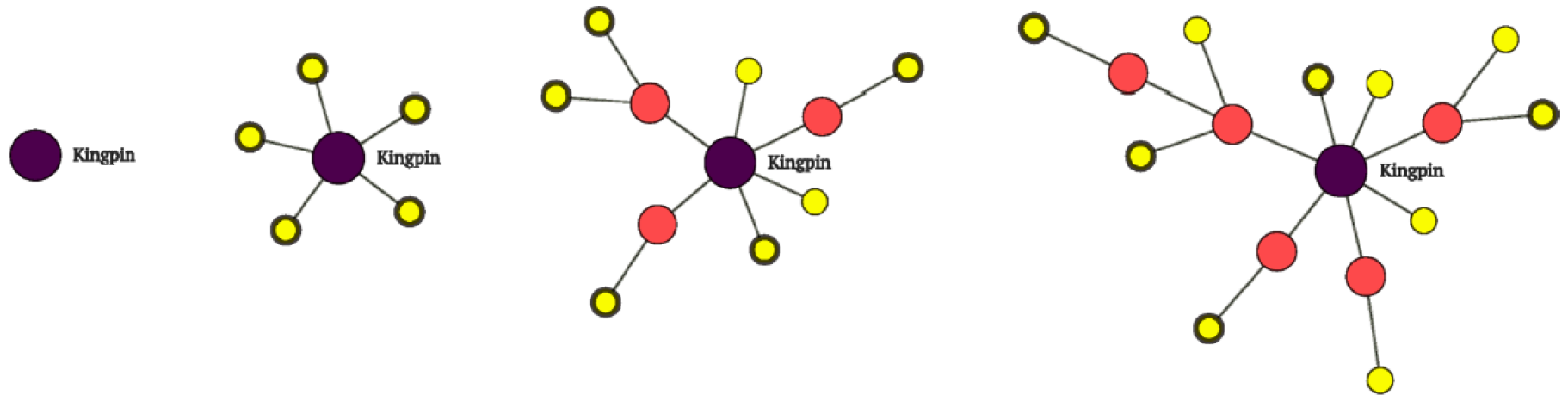
Juan Pablo Antonio LONDONO RAMIREZ DOB 15 Feb 1965 CC 1828778 (Colombia) RFC LON80605150011 (MX)	Catalina Alexandra MONTOYA ZAPATA DOB 28 Apr 1964 CC 3229453 (Colombia)	Hector Mario CIFUENTES VILLA DOB 28 Nov 1964 CC 7163353 (Colombia)	Teresa de Jesus CIFUENTES VILLA DOB 13 Jun 1953 CC 3250252 (Colombia) CURP CIV350613MNEFLR06 (MX)	Jorge Andres CIFUENTES OSORIO DOB 29 Mar 1985 CC 8079674 (Colombia)
Claudia Emilia LOPEZ MIELA DOB 18 Dec 1972 CC 42104723 (Colombia)	Juan Fernando GONZALEZ VARGAS MULLO DOB 5 Nov 1966 CC 15348215 (Colombia)	Paula Andrea VARGAS CIFUENTES DOB 23 May 1976 CC 6877978 (Colombia) CURP VACP39023MNERFL00 (MX)	Edison Felipe VARGAS CIFUENTES DOB 19 Aug 1978 CC 7993460 (Colombia) CURP VACE78081HINERFD01 (MX)	
Ruben RAYGOSA CONTRERAS DOB 17 Mar 1978 CURP RACK700317UCYN089 (MX)	Irma Mery BASTO DIEZGADO DOB 9 Apr 1967 CC 2096430 (Colombia)	Alea Yocellia PACHECO PARRA DOB 23 Feb 1982 CC 5286649 (Colombia)	Mirya Yareth RESTREPO ZAPATA DOB 13 Dec 1973 CC 4382354 (Colombia)	Yenny Mabel SANCHEZ PUENTES DOB 19 Dec 1967 CC 5190869 (Colombia)
				Alex Patricia BOLDAN CARDONA DOB 9 Dec 1969 CC 4372334 (Colombia)
				Paulo Alberto GOMEZ ZULLAGA DOB 20 Jun 1967 CC 7168566 (Colombia)

Cifuentes Villa, Colombia



La familia Michoacana, Mexico

How to stop the growth of a criminal network?



growth and containment

Network growth

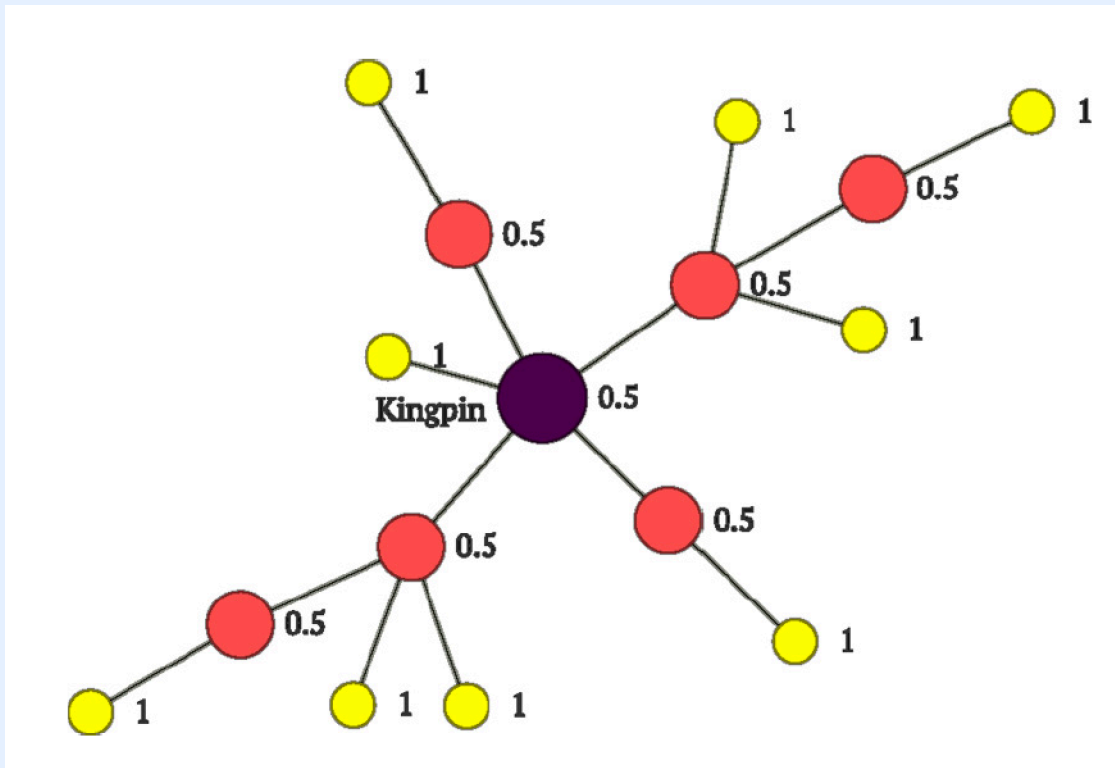
- Start with “kingpin”
- Grow hierarchically -- k recruits at each time step
 - Preferential attachment at “street criminals”

Probability of attachment for each node $w(j,t)$
Distance from “street” $\sigma(j,t)$

$$w(j,t) = \frac{1}{\sigma(j,t) + a}$$

If node j on street $\sigma(j,t)=0$, $w(j,t) = 1/a$
If node j very far from street $\sigma(j,t) \gg a$, $w(j,t) \sim 0$

Network growth



$$w(j,t) = \frac{1}{\sigma(j,t) + a}$$

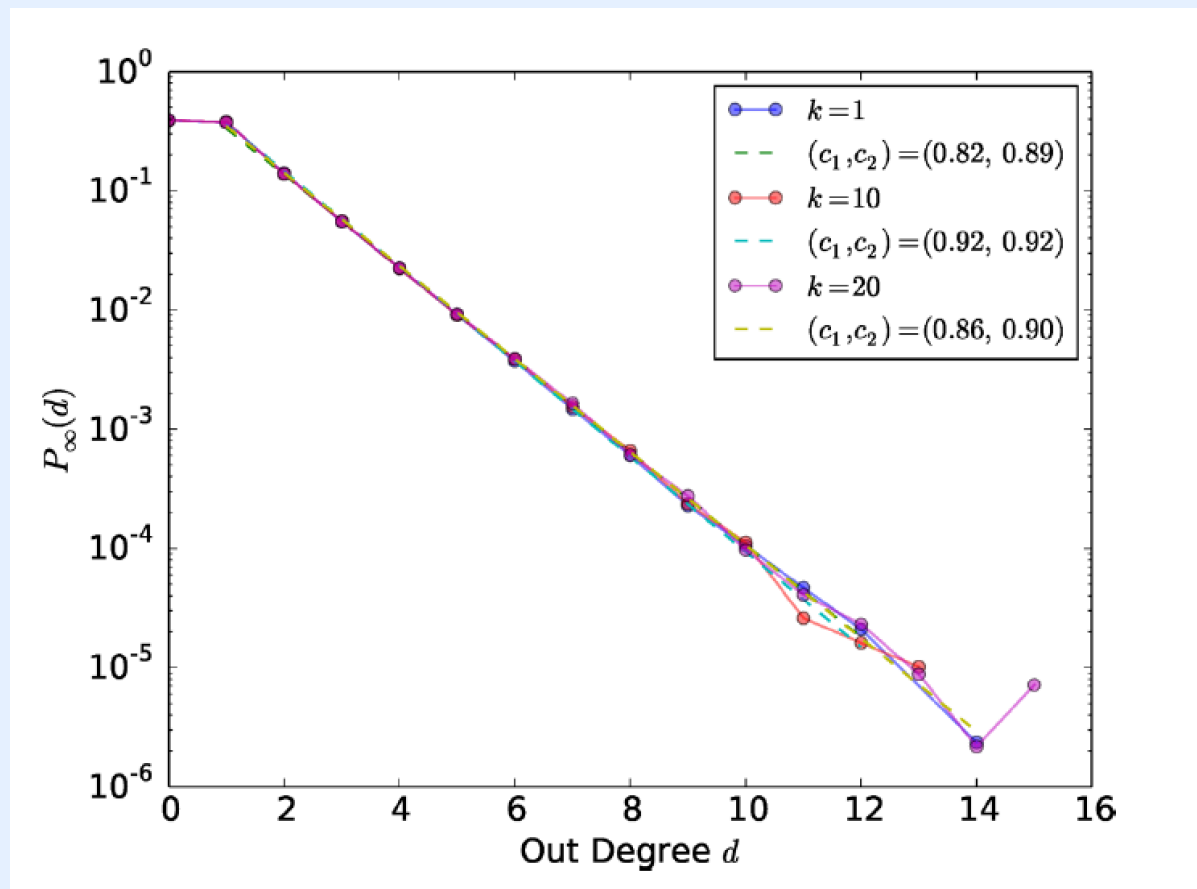
$k=5, a=1, t=3$
Street criminals
yellow

kingpin $\sigma=1, w=1/2$
street criminals $\sigma=0, w=1$

Node distribution

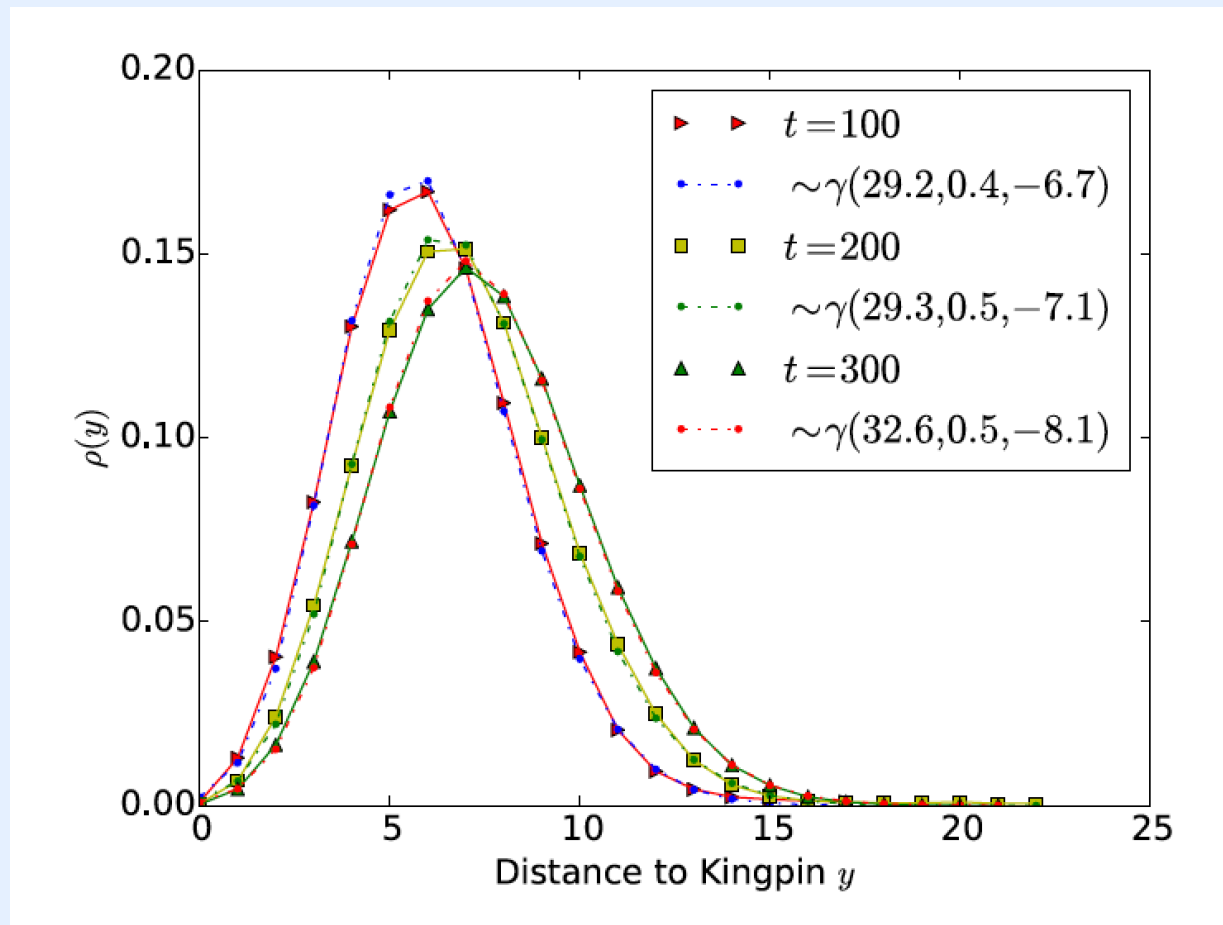
$P(d,t)$ = probability any node has d underlings at time t

For $t \gg 1$, $P(d,t) \sim c_1 \exp[-c_2 t]$



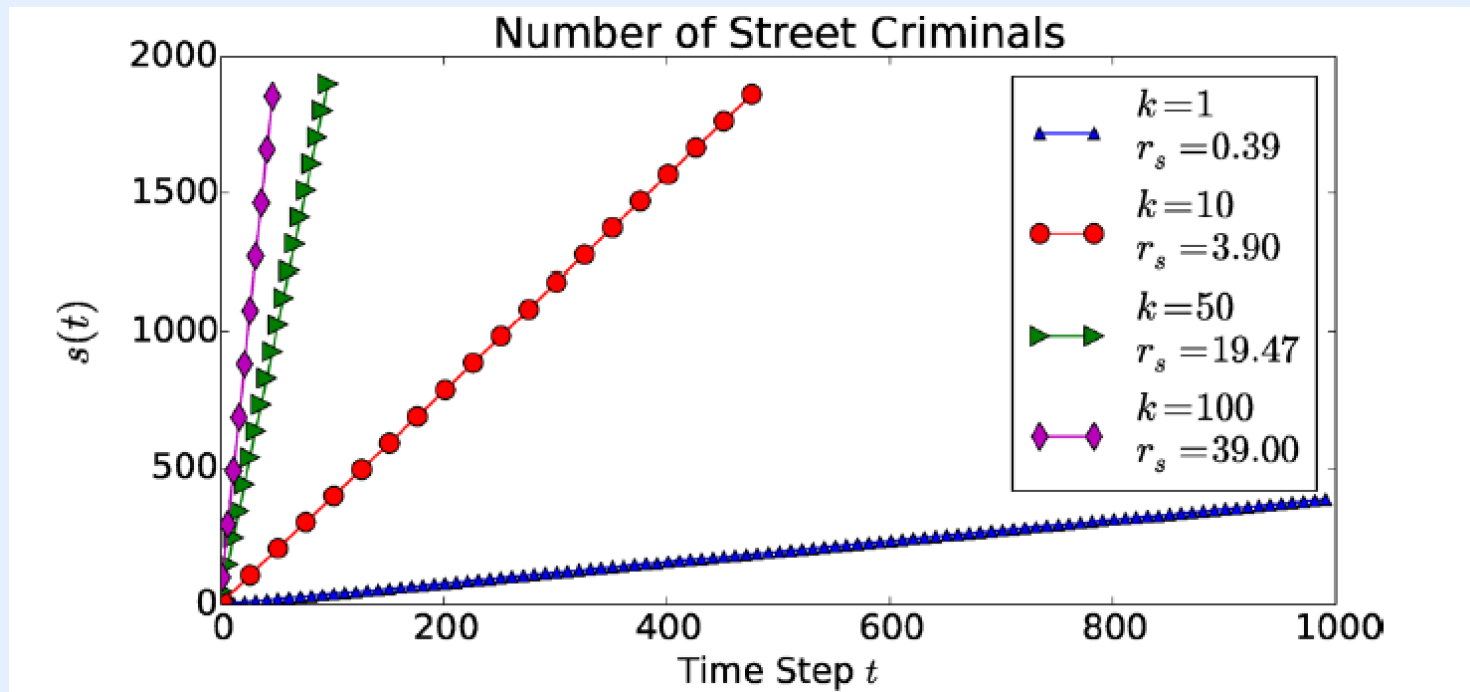
Distance from kingpin

On averages increases with time and follows a shifted Γ probability density



Number of street criminals $s(t)$

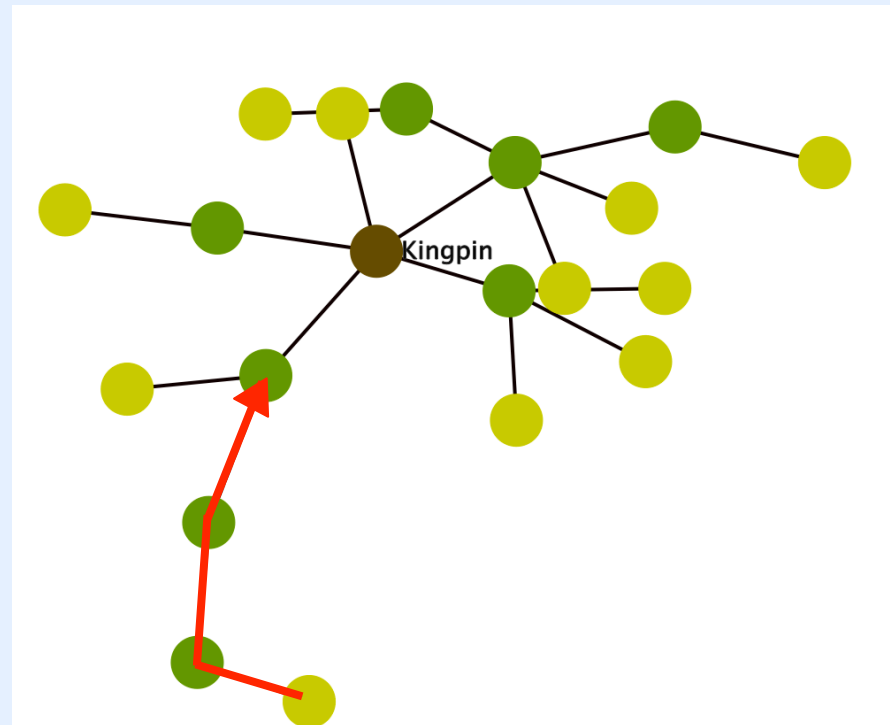
increases linearly with time, and with k



$$s(t + 1) \simeq s(t) + \frac{\sum_{j \in \mathcal{C}(t)} w(j; t) - s(t)}{\sum_{j \in \mathcal{C}(t)} w(j; t)} k.$$

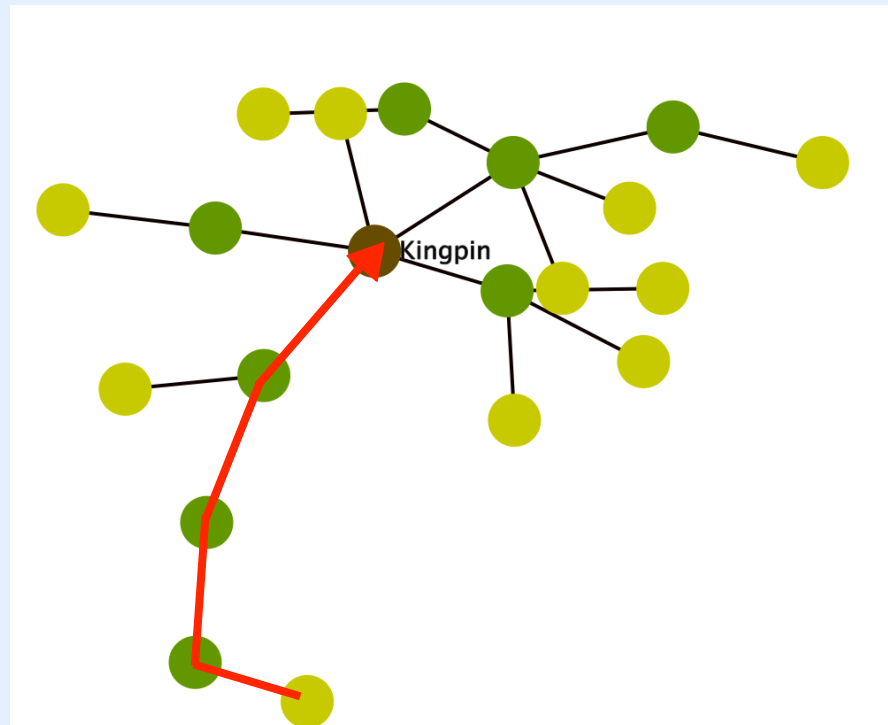
Network containment

- **Police** always start “investigating” street criminals
 - Move up via self-avoiding random walks
 - Dark network – structure unknown
 - Network is still growing



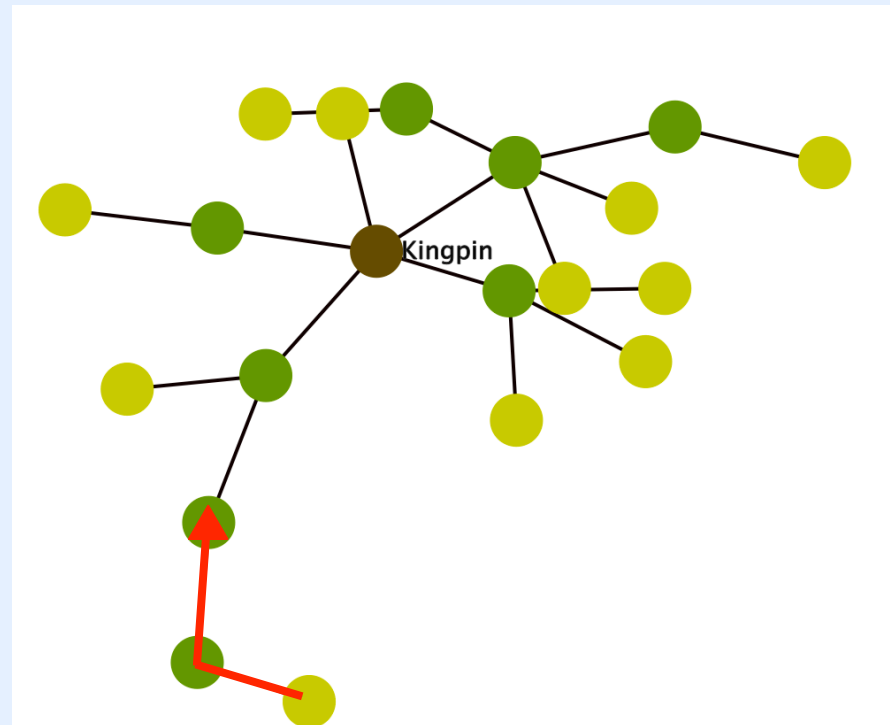
Three strategies

1. Stop when kingpin is reached
2. Stop if criminal of distance q from street is reached
3. Stop after p steps



Three strategies

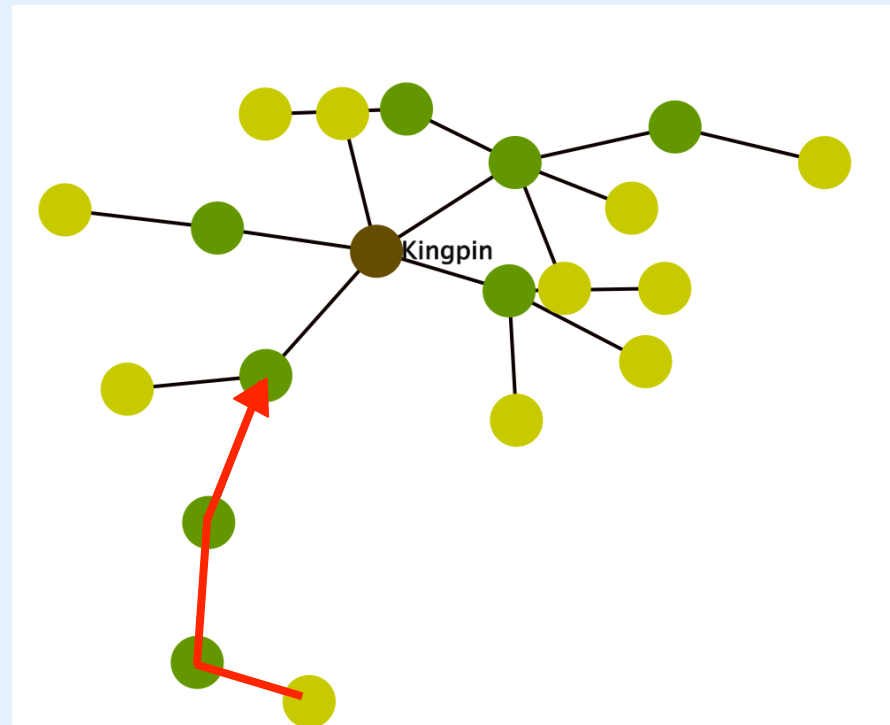
1. Stop when kingpin is reached
2. Stop if criminal of distance q from street is reached
3. Stop after p steps



$q=2$

Three strategies

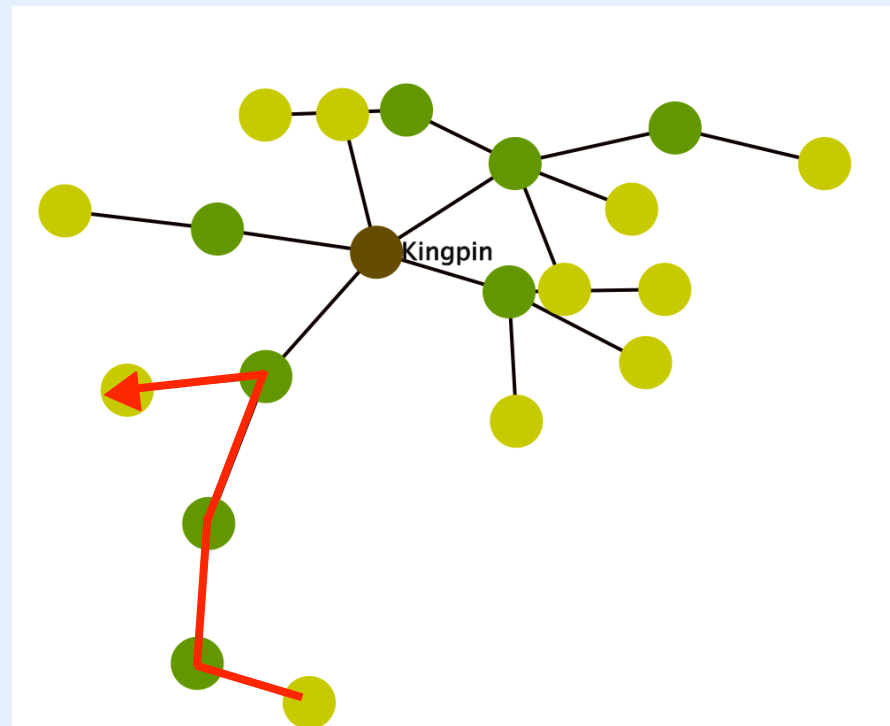
1. Stop when kingpin is reached
2. Stop if criminal of distance q from street is reached
3. Stop after p steps



$p=3$

Reaching dead-ends

If number of investigations until stopping is too large,
higher risk of dead-ends



Eradication probability

2. Stop if criminal of distance q from street is reached
grow network until $n=2000$ people

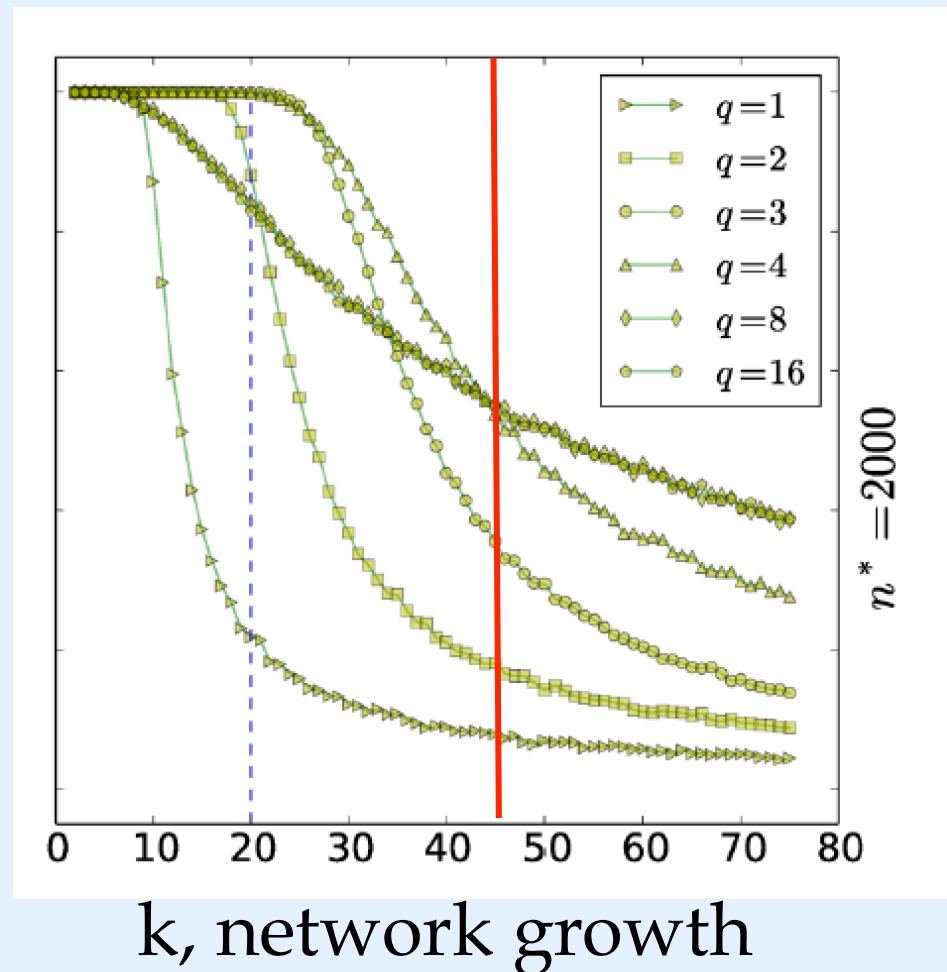
Eradication
decreases for k

$P=1$

For small $k \sim 40$, q
intermediate is
optimal

For large $k > 40$, q
large is optimal

$P=0$



Lessons?

If network is growing fast,
Aim to catch more senior criminals
more risky, more rewards

If network is growing slowly,
Aim to catch lower level criminals
less risky, reach kingpin slowly but surely

Summary and conclusions

Simplified models, mathematically tractable

Basic concepts from sociology, criminology, anthropology analyzed through math tools

Some validation through data, experiments

Predictions, discussion, ideas,
more questions to be asked

Integration with data?

Thank you

Martin B. Short (Georgia Tech)

Andrea Bertozzi (UCLA)

Lincoln Chayes (UCLA)

Yaoli Chuang (CSUN)

Tom Chou (UCLA)

Mike McBride (UCI)

Ryan Kendall (UCI)

Richard Dekmejian (USC)

Bijan Berenji (UCLA)

P. Jeff Brantingham (UCLA)

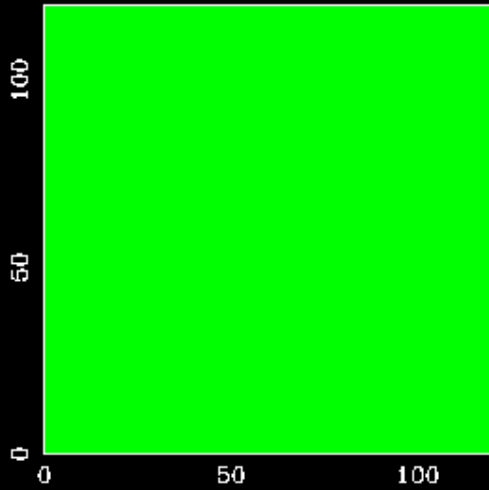
George Tita (UCI)

Charlie Marsak (UCLA)

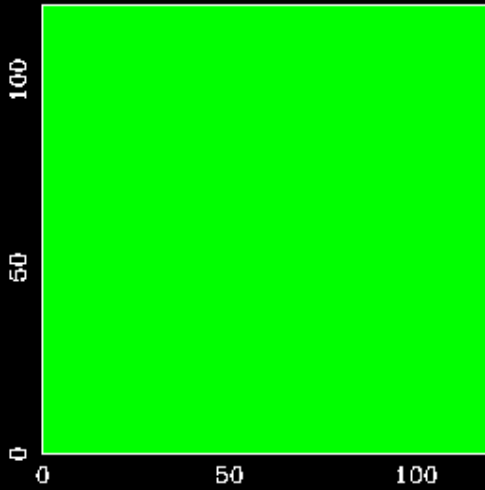
Milind Tambe (USC)

Discrete simulation

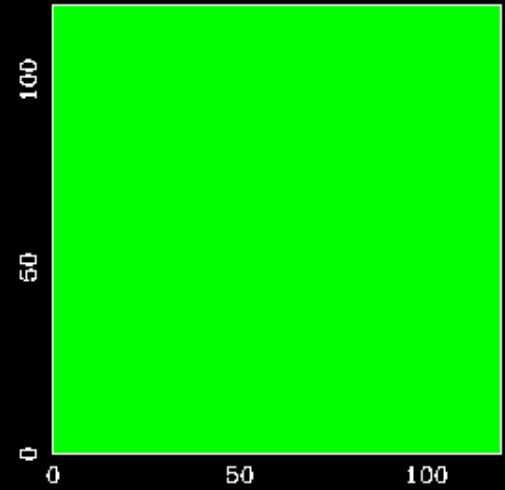
$B(x,y,t)$, $t=0$ days



$A(x,y,t)$, 14414 criminals



$E(x,y,t)$, min=0, max=0, avg=0



Attractiveness vs. Crimes

Best Response Analysis

Strategies are not chosen by imitation
but depend on payoff maximization

Once in a game, the first player will choose to victimize only if his/her expected payoff is higher than 1.

Once victimized, the victim will choose whether to report or not in order to improve his/her payoff odds.

Informants do not necessarily drive the system to utopia
(not always a best response)

But it is a best response for low enough punishment to the informant