Case studies from mathematical models of criminal behavior

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1. Crime hotspots

2. An informant and a criminal

3. Recidivism and rehabilitation policies

4. Criminal networks
1. Crime Hotspots

Spatio-temporal clusters of crime

Burglary, grand theft auto

Time scales: hours to months
Geographical scales: a few city blocks
"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
“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.”

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.
Repeat victimization

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

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

Merseyside

Temporal decay of residential burglary revictimisation over a 10 month period.

Brent, London
Your neighbors are at risk as well!

Residential burglary, Long Beach

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

A=8

A=4

A=3

A=5

A=2, start

A=9

A=14

A=7

A=10
i) Site not very attractive, move

A=8

A=4

A=2, start

A=5

A=10

A=14

A=7

A=9

A=3
i) Site not very attractive, move
ii) Attractive site, steal

\[ A=14, \text{ start} \]

\[ A=8 \]

\[ A=5 \]

\[ A=4 \]

\[ A=2 \]

\[ A=7 \]

\[ A=3 \]

\[ A=9 \]

\[ A=10 \]
ii) Attractive site, steal

A=8

A=5

A=14, steal, leave

A=4

A=2

A=7

A=3

A=9

A=10
A increases close to the theft site

- $A = 8$
- $A = 4$
- $A = 3$
- $A = 5 + 1$
- $A = 2$
- $A = 9$
- $A = 14 + 2$
- $A = 7 + 1$
- $A = 10$
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

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ell$</td>
<td>Grid spacing</td>
</tr>
<tr>
<td>$\delta t$</td>
<td>Time step</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Dynamic attractiveness decay rate</td>
</tr>
<tr>
<td>$\eta$</td>
<td>Measures neighborhood effects (ranging from 0 to 1)</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Increase in attractiveness due to one burglary event</td>
</tr>
<tr>
<td>$A_s^0$</td>
<td>Intrinsic attractiveness of site $s$</td>
</tr>
<tr>
<td>$A_s$</td>
<td>Rate of burglar generation at each site</td>
</tr>
</tbody>
</table>
Simulations

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

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

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

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

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

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

\[
A^* = A_0 + \Gamma
\]

\[
\rho^* = \frac{\Gamma}{\Gamma + A_0}
\]

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

\[
\rho = \rho^* + \delta_\rho e^{\sigma t} e^{i k \vec{x}}
\]
Linear Stability Analysis

\[ \sigma(k) \]

\[ \sigma - \text{imaginary} \]

\[ \sigma - \text{real} \]

Typical wavenumber \( k^* \) -- Typical distance \( \lambda = 2\pi/k^* \)
Hotspot separation

\[ \lambda = \frac{2\pi}{k^*} \quad \text{-- fitted vs. simulated data} \]

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” \( \delta < 1 \)
   
   \[
   \text{Victim} \quad 1-\delta \quad \text{Victimizer} \quad 1+\delta
   \]

4. Reporting?
   
   If the victim is a \textit{villain} or an \textit{apathetic} no reporting
   end of round - start over
   
   If the victim is a \textit{paladin} or an \textit{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 $\omega$. The $\delta$ “loot” is returned to the victim. The victimizer is punished by $\theta$.

4. Victimizer is free with probability $1-\omega$. The $\delta$ “loot” is kept by the victimizer. The victim gets extra loss $\varepsilon$ 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

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

\[ I_0 = 40, \quad A_0 = P_0 = 0, \quad V_0 = 960 \]
\[ I_0 = A_0 = 0, \quad P_0 = 400, \quad V_0 = 600 \]

Stochastic

Deterministic

\[ \theta = 0.6, \quad \varepsilon = 0.2, \quad \delta = 0.3 \]
\[ N = 1000 \]

Paladins “win”
UTOPIA

Villains “win”
DYSTOPIA
Upon closer inspection

\[ N = 100 \]
\[ A_0 = 0, \quad V_0 = N - P_0 - I_0. \]

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 is 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

\[
\text{Cost} = \text{cost to convert informants} + \text{losses to society due to crime}
\]

Stochastic vs. deterministic

OPTIMAL CONVERSION
What do real people do?
Here is what UCI college kids do

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

16 experiments, 10 treatments, ~ 400 students

Learning rounds, inertia, ‘parallelized’
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

- Total state and federal inmates in 2010
  1.6 million

NOTE: Data for Connecticut and Oregon not available

© 2011 MCT
Source: U.S. Bureau of Justice Statistics
Graphic: Judy Treible

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
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

\[ N_0, N_1, N_2, \ldots, N_k, \ldots \]
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 $i$

$$k_u \text{ unpunished crimes} \quad k_p \text{ punished crimes}$$

$$k_{\text{total}} = k_u + k_p$$

- Personal history - $p_i$
- Societal input - $s_i$
- Attenuation due to rehabilitation – $a_i$

$$p_{\text{Crime}} = \left( \frac{p_i + s_i}{2} \right) a_i$$
Mathematical choices

\[ p_i = \frac{p_0 + k_u}{k_u + p_0 + \theta k_p} \]

\[ s_i = \sum_{k \neq 0} N_k + U \]

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

\[ p_{\text{Crime}} = \left( \frac{p_i + s_i}{2} \right) a_i \]

\[ \theta \text{ punishment} \]
\[ \text{unpunished crimes} - k_u \]
\[ \text{punished crimes} - k_p \]

Crime generates more crime

\[ h \text{ incentives} \]
\[ \tau \text{ time duration} \]

After crime: punish with probability \( \alpha = 1/4 \)
After the crime

If no crime committed: reform with probability

\[ P_{\text{reform}} = \frac{\alpha P}{N} \]

If a crime committed

if not arrested/punished

don’t reform

\[ P_{\text{reform}} = 0 \]

if arrested/punished

reform with probability

\[ P_{\text{reform}} = \frac{1}{2} \left( \frac{\alpha P}{N} + \frac{\theta k_p}{k_u + p_0 + \theta k_p} \right) \]
### Variables/Parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P$</td>
<td>paladins</td>
</tr>
<tr>
<td>$U$</td>
<td>unreformables (who have been punished $R$ times)</td>
</tr>
<tr>
<td>$N_0$</td>
<td>neutral citizens that have committed no crimes</td>
</tr>
<tr>
<td>$N_k$</td>
<td>citizens that have committed $k = k_u + k_p$ crimes</td>
</tr>
<tr>
<td>$k_u$</td>
<td>number of unpunished crimes</td>
</tr>
<tr>
<td>$k_p$</td>
<td>number of punished crimes</td>
</tr>
<tr>
<td>$h$</td>
<td>parameter quantifying resources</td>
</tr>
<tr>
<td>$\tau$</td>
<td>duration of intervention</td>
</tr>
<tr>
<td>$\theta$</td>
<td>severity of punishment</td>
</tr>
<tr>
<td>$p_0$</td>
<td>punishment amplitude parameter</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>arrest and conviction probability</td>
</tr>
<tr>
<td>$R$</td>
<td>maximum number of punished crimes</td>
</tr>
</tbody>
</table>

Irreversible system, very sensitive to initial conditions
Runs

400 individuals, 25 replicas

\[ \tau = 2 \quad p_0 = 0.1 \quad \alpha = \frac{1}{4} \quad R = 3 \]

vary \( h, \theta \)

\( \text{IC0} : 400 \text{ in } N_0 \text{ at time } t=0 \)

\( \text{IC1} : 200 \text{ in } N_0, 200 \text{ in } N_1 \text{ at time } t=0 \)

Parallel updates
Results
Total resources are finite!

Carrot, stick or both?

The carrot:
Rehabilitation resources $h\tau$

The stick:
Punishment resources $\theta$

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 indeces $k_u, k_p$

$N_k \rightarrow N_{ku,kp}$

$p_{crime} \rightarrow c_{ku,kp}$

$p_{reform} \rightarrow r_{ku,kp}$
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 \( k_p = 1, \cdots, R - 1 \)

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

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

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

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

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

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

\[ t - t_{\text{last}} = t / k_p \]
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

$\tau$ time for rehabilitation

$\varTheta$ punishment
A qualitative match, IC0
4. Criminal Networks

Organized crime: complex hierarchical structures

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

Organized Crime Family

Boss

Underboss (Controller)

Caporegime (Lieutenant)

Caporegime (Lieutenant)

Caporegime (Lieutenant)

Soldiers (Members)

Through threats, assault, murder and payoffs...

Legitimate Businesses:
- Food Products
- Real Estate
- Restaurants, Bars
- Garbage Disposal
- Government Manufacturing
- Waterfront
- Securities
- Vending Machines

Illegal Activities:
- Gambling (Numbers, Policy, Dice, Bookmaking)
- Nuns
- Laundering
- Labor Trafficking
- Extortion

Cali, Sinaloa Mexico
How to stop the growth of a criminal network?
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 \( \sigma(j,t) >> a \), \( w(j,t) \sim 0 \)
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

\[ P(d,t) = \text{probability any node has } d \text{ underlings at time } t \]

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 $\Gamma$ probability density

![Graph showing the distribution of distances from the kingpin over time.]
Number of street criminals $s(t)$ increases linearly with time, and with $k$

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

For small k~40, q intermediate is optimal

For large k>40, q large is optimal

P=1

P=0

k, network growth
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)
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Discrete simulation

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.