Agent-based Modeling of Social Systems

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Outline

1. Modeling of social systems: what, why, how?
2. Overview of agent-based methodology
3. A gallery of agent-based models:
   - Epstein's social violence model
   - Gauteng province service protests
   - Inter-communal violence
   - Prosperity and well-being
4. Capabilities and limitations
5. Conclusions and future prospects

How can policy-makers make intelligent decisions that improve social conditions?

Prerequisites for making intelligent policy decisions

Policy-makers must:

- *Understand* the current situation;
- *Predict* the results of any proposed changes in policy
- *Evaluate* the impact of these results on quality of life

The potential role of mathematical models in social policy

Mathematical modeling provides:

- *Understanding:*
  - a precise language for *describing* situations
  - a method for *analyzing* situations
- *Prediction:*
  - A tool to assess strategies for *changing* and/or *controlling*
- *Evaluation:*
  - A means for comparing strategies in terms of quantifiables (income, crime rate, etc.)

Characteristics of Social Mathematics

- Sociology is concerned with the collective behavior of humans
- Individual human behavior is extremely complex
- However, collective behavior may show *statistical* regularities
- Social mathematics is essentially *statistical*

Descriptive Models in Social Mathematics

Descriptive models use data to find levels of and relationships between various factors:

- Tests of significance, confidence intervals, regression
- An enormously important tool in determining social policy
- A strong and progressive democracy depends on the population having a basic understanding of statistics

Dynamical Models in Social Mathematics

Dynamical models attempt to explain social phenomena in terms of underlying forces and motivations

- Example: macro- and microeconomic models
- Require assumptions (expert knowledge)
- Have built-in limitations
  - Prone to over-simplification
  - Can only capture first-order effects
  - Can only suggest, not dictate
  - Tend to be qualitative, not quantitative

“Bursty” social behavior

- Fads (viral web sites, etc.)
- Outbursts of civil violence (such as riots) due to a variety of causes –
  - Political (Arab Spring 2010)
  - Social (London 2011)
  - Ideological (Movie riots 2012)
  - Economic/Material (Cameroon food riots 2007-08; Gauteng province service protests)
- Are there mathematical models that can exhibit such “bursty” behavior?

Agent-based Computational Models

Individuals in a population can be modeled as *agents*

- Agents interact with each other
- Interactions are highly individual, but tend to follow certain regular patterns

Agent-based systems can be programmed on the computer

- Each agent is represented as a data structure
- Interactions can be programmed
- Typically some randomness is included to account for individuality.

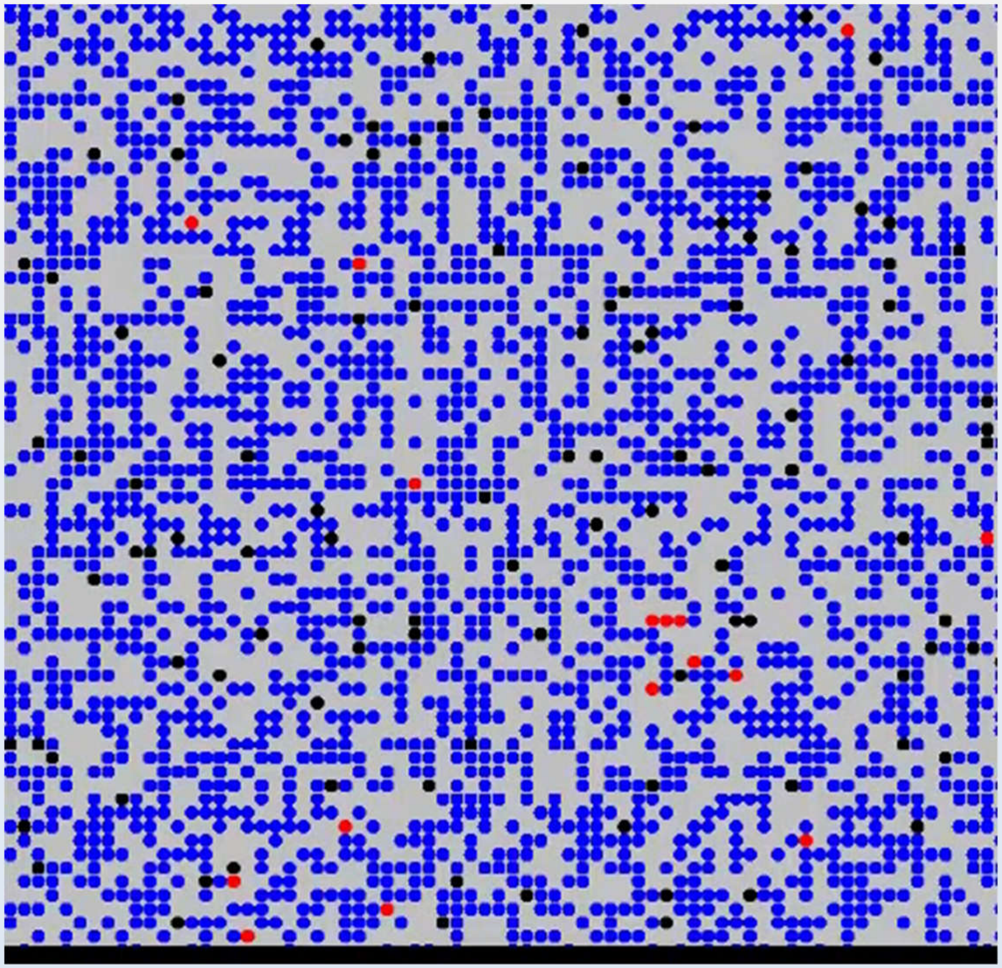
Example 1: the Epstein model

Agent-based model formulated by Joshua Epstein[1]

- Technique previously used to model spread of disease via infective contact
- Views outbursts as the cumulative result of unplanned, spontaneous interactions of "agents" with their immediate neighbors.
- Violent agents are arrested by "cop agents"
- Individuals are incited to violent action if their neighbors are active; and are inhibited if cop agents are around

[1] Epstein, Joshua M., Modeling civil violence: An agent-based computational approach, PNAS, May 14, 2002; vol. 99, suppl. 3, pp. 7243-7250.

Epstein Model: what it looks like



- Populace agents:
  - “inactive” (blue) or “active”
  - “jailed” agents don’t appear
- Cop agents (black):
  - “Patrol” and arrest the active agents that they see

Populace agents' decision rule

At each time step, each agent *a* decides to go active if:

$$G_a - R_a \cdot P_a > \Theta$$

Where

G_a = agent's *Grievance*

R_a = agent's *Risk aversion*

P_a = agent's *Arrest probability*

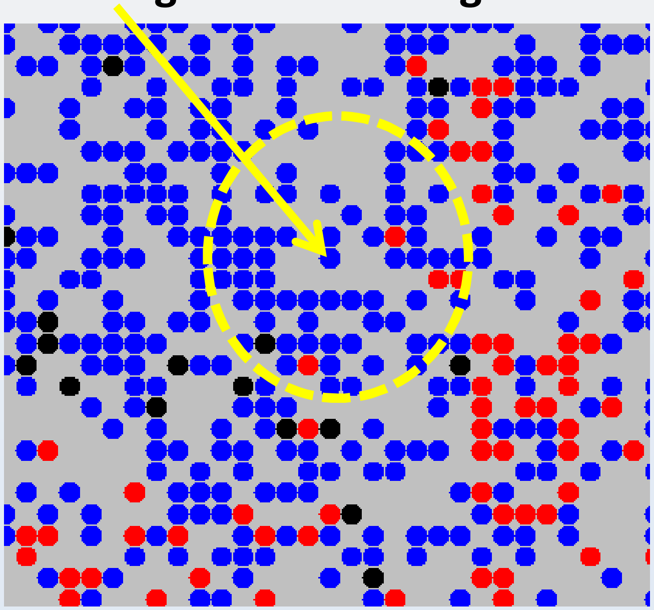
Θ = fixed *threshold*

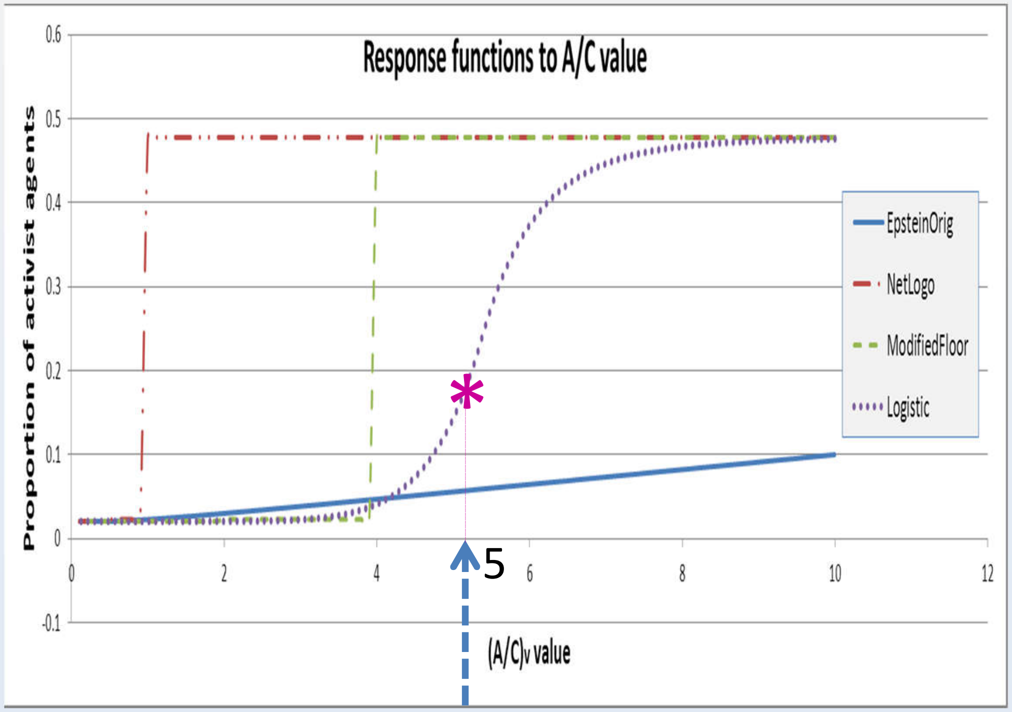
G_a, R_a, P_a are assigned on a per-agent basis according to probability distributions.

P_a depends on the ratio (# active agents /# cop agents) within agent's vision (P_a is a *nonlinear* function)

A simplified picture

Will this agent decide to go active?





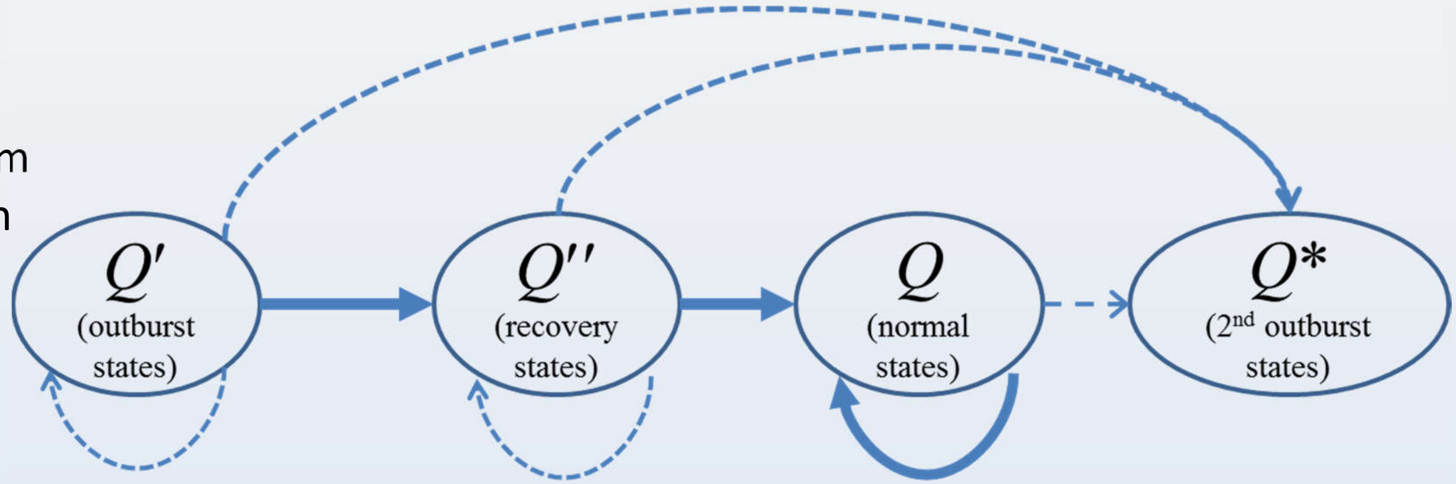
The agent sees 1 cop & 4 actives within his "field of vision"

[4(actives) + 1(self)] / 1(cop) = 5

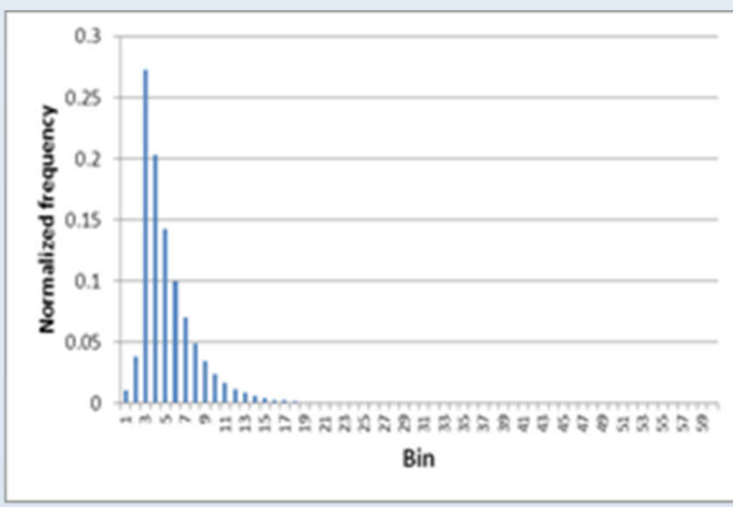
Model says: *unpredictable* outbursts

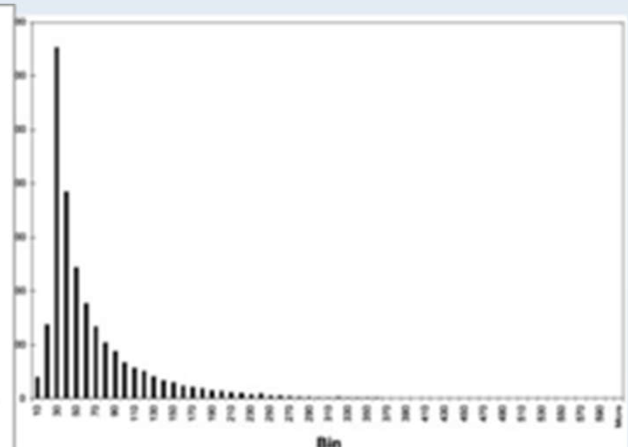
(Markov property)

Model moves from state to state with *fixed* transition probabilities



Probability distribution of outburst waiting times



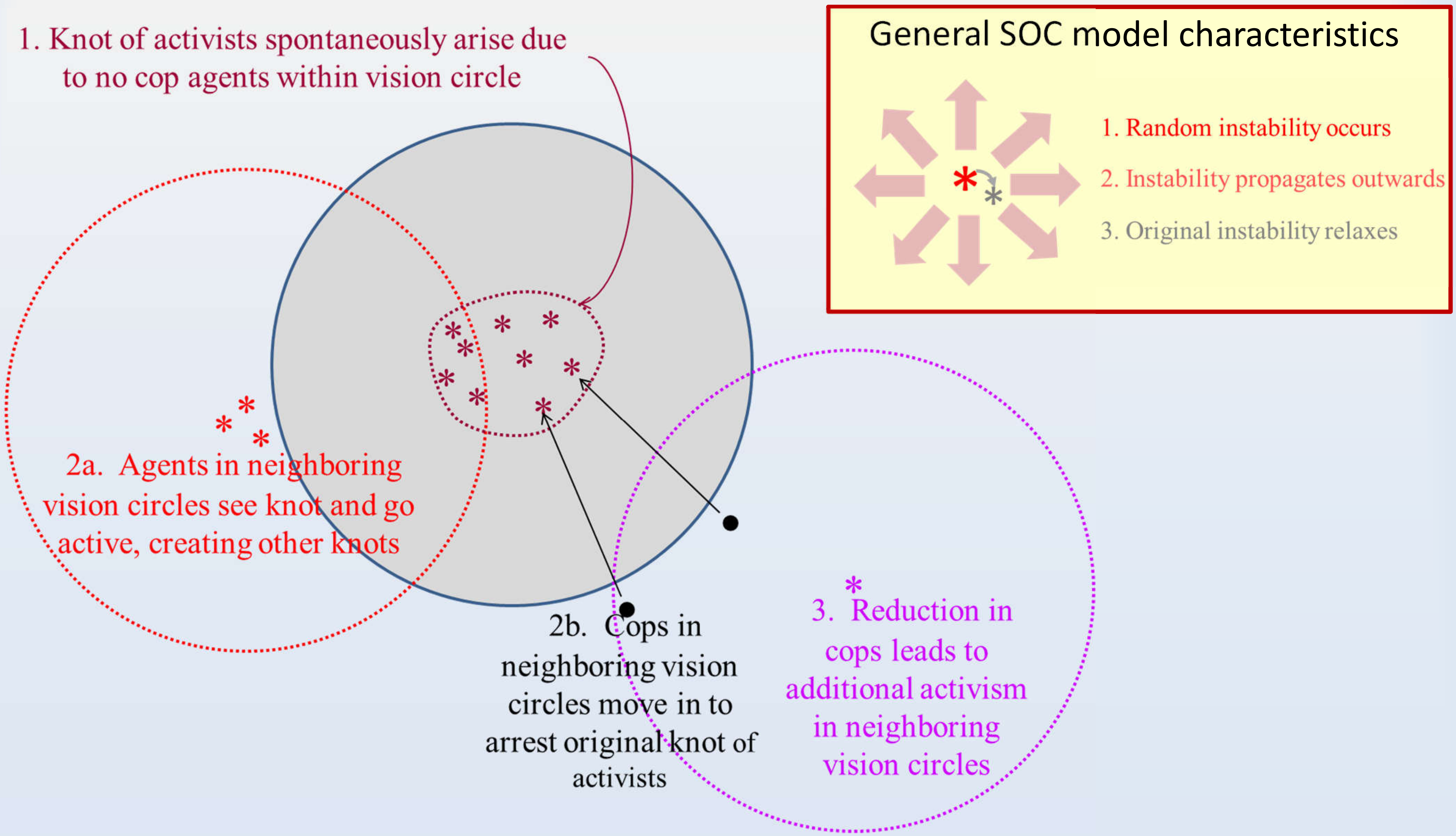


Simplified model (above)

Observed (by Epstein)

Model says: “Earthquake” size distributions

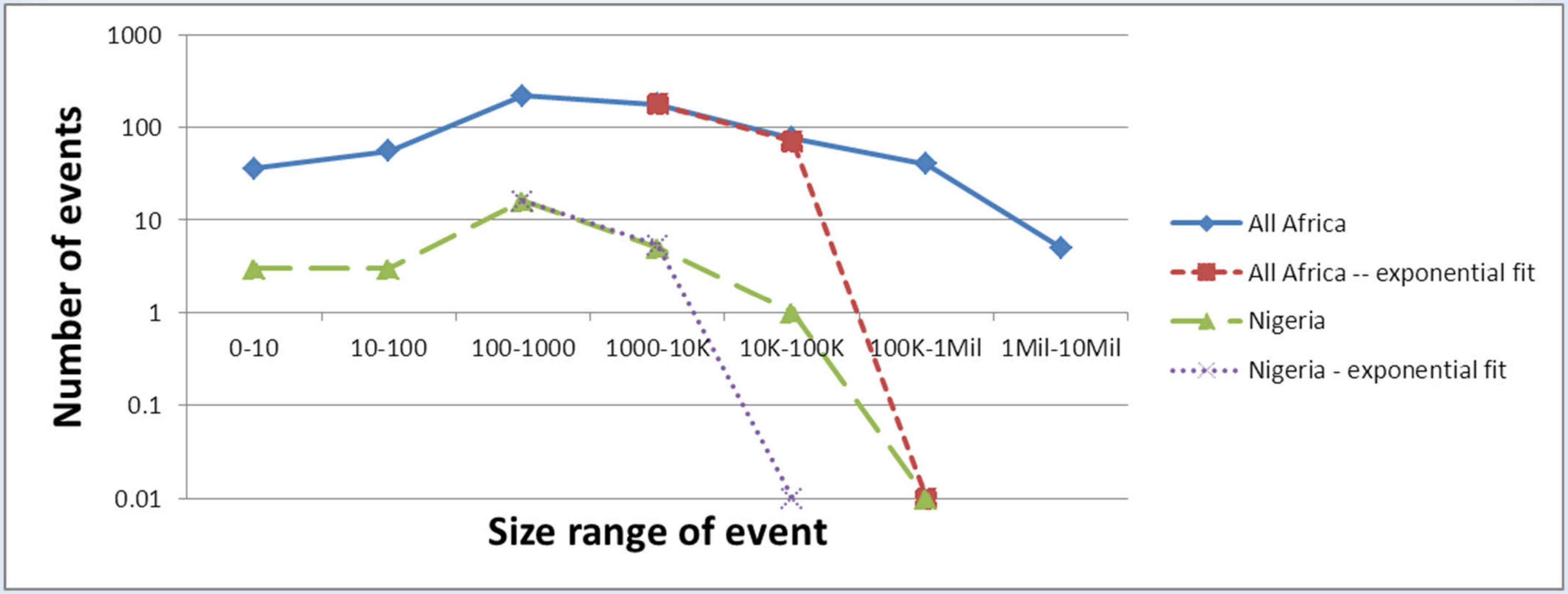
(Self-Organized Criticality)



Power Law: $\Pr[\text{ outburst size} = Z] \propto Z^{-a}$, *or* $\log \Pr[N \leq \text{ outburst size} \leq 10N] \approx K - \beta \log N$

Real-life riot-size distributions

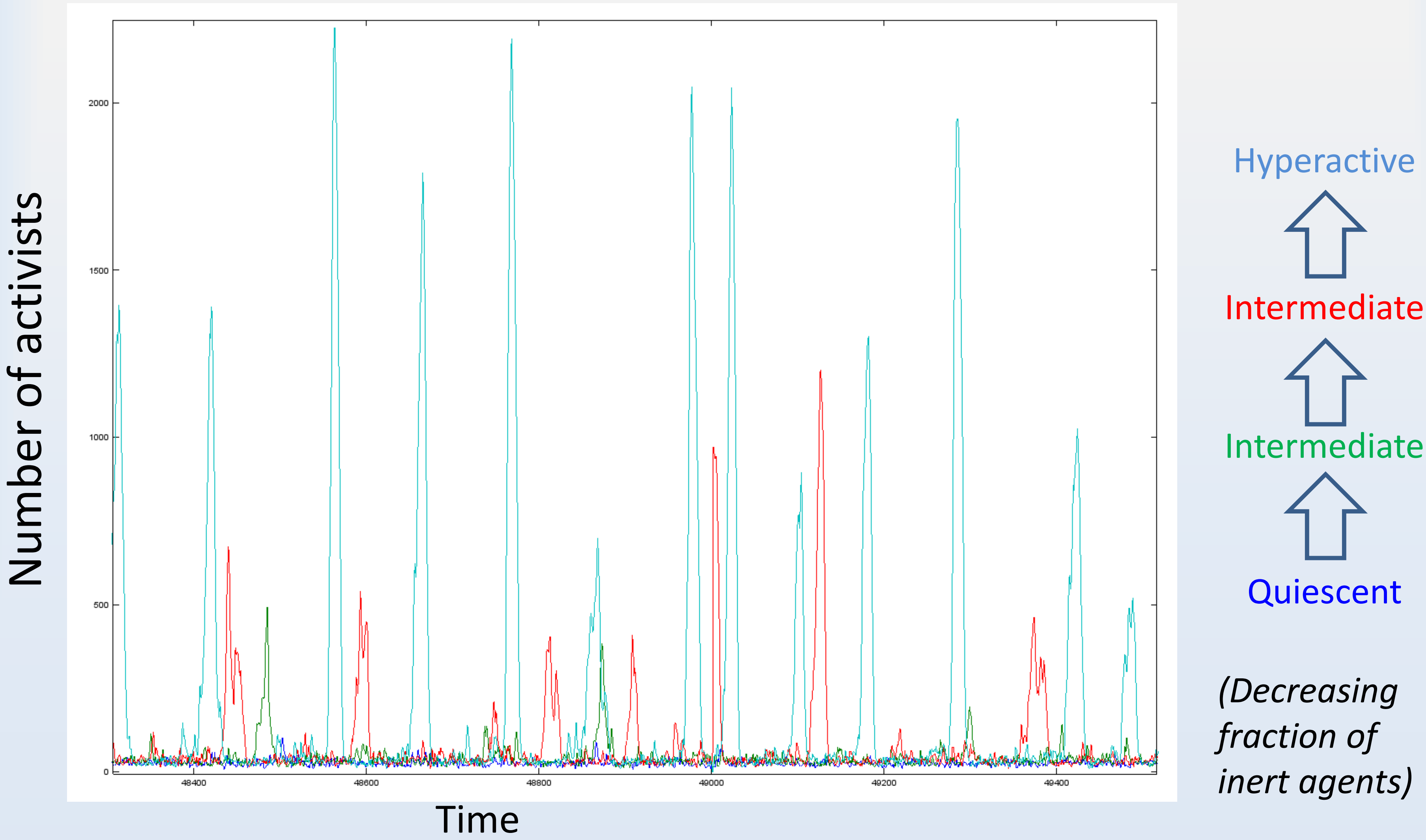
Number of riot events versus size range for riots in Africa and Nigeria(1997-2011), from ACLED dataset (www.acleddata.com)



Power-law fits <u>much</u> better than exponential

$\Rightarrow$ "Blue-moon" outbursts are not impossible

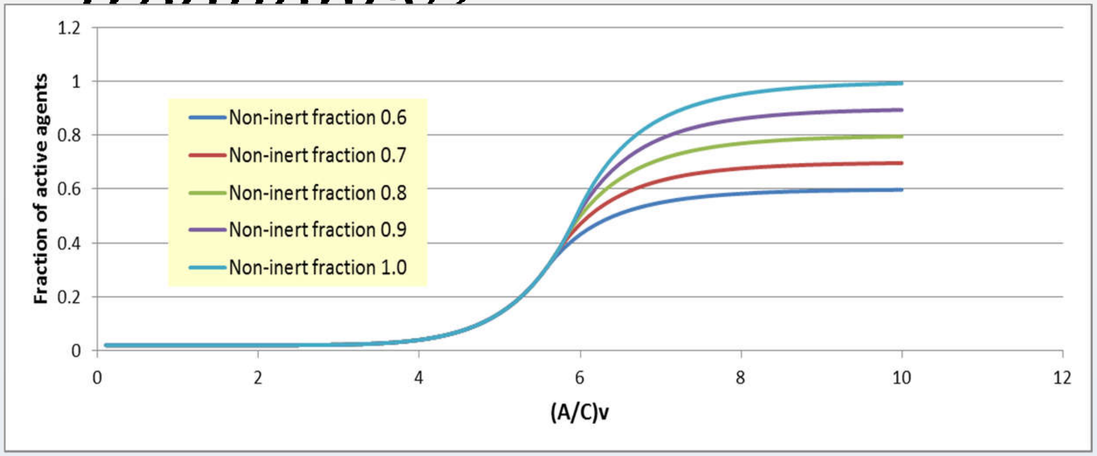
Modes of outburst behavior



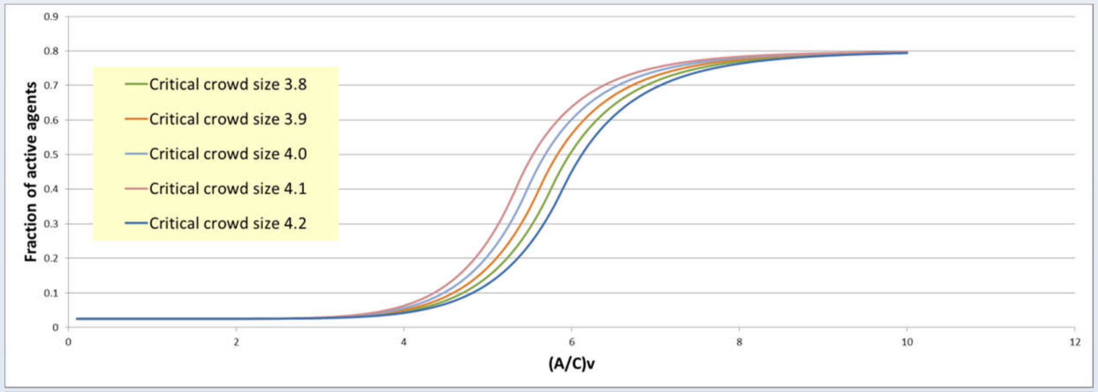
Continuous transition between modes as parameters vary

What determines outburst size and frequency?

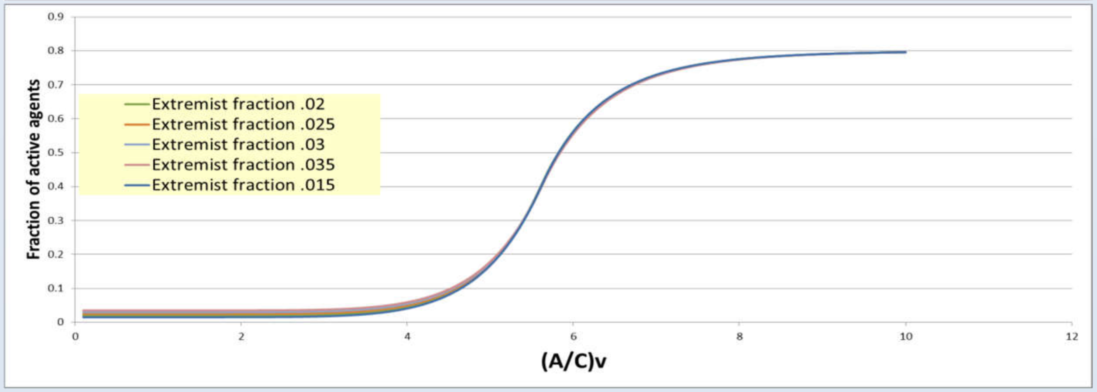
“Excitable” population proportion



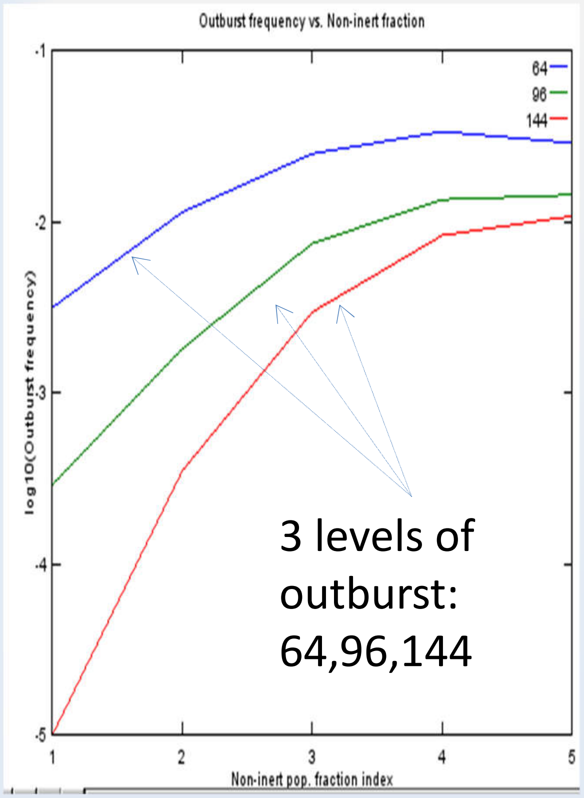
Critical crowd size



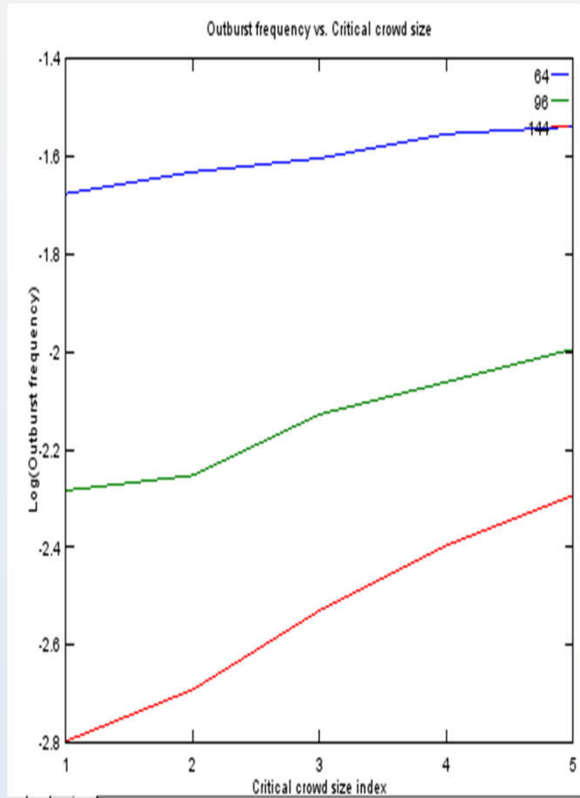
“Hothead” population proportion



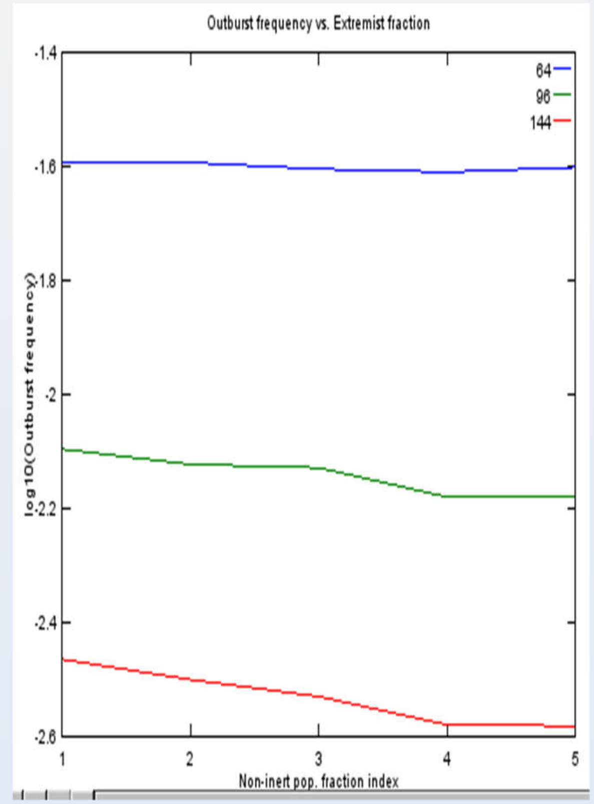
(log of) Outburst frequency



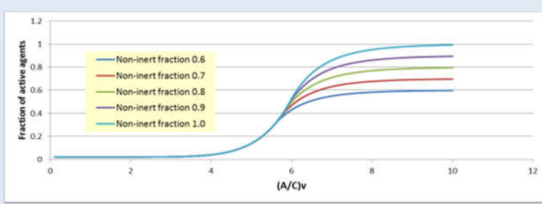
Excitables



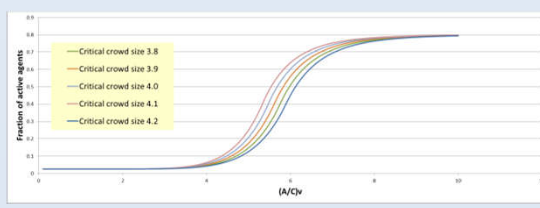
Critical crowd side



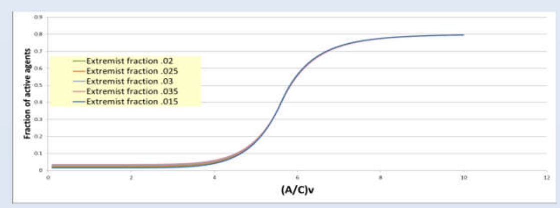
Hotheads



Sharp increase, then saturates

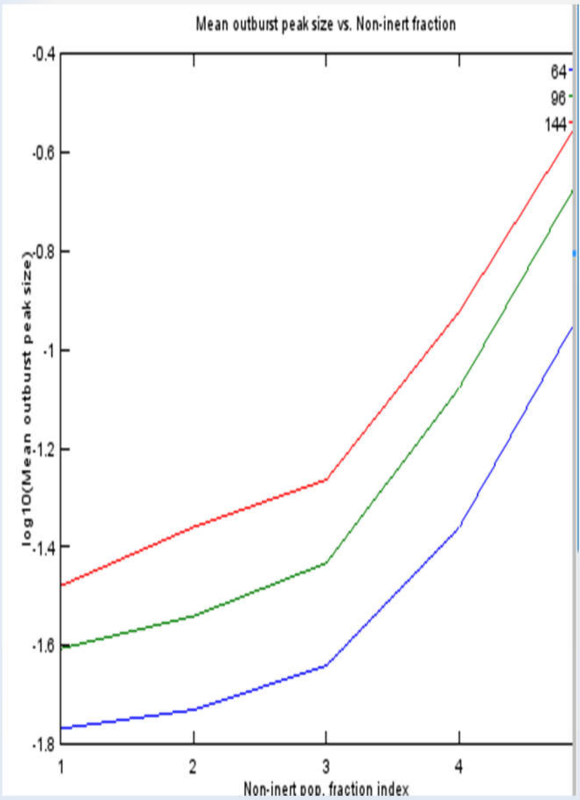


Steady increase

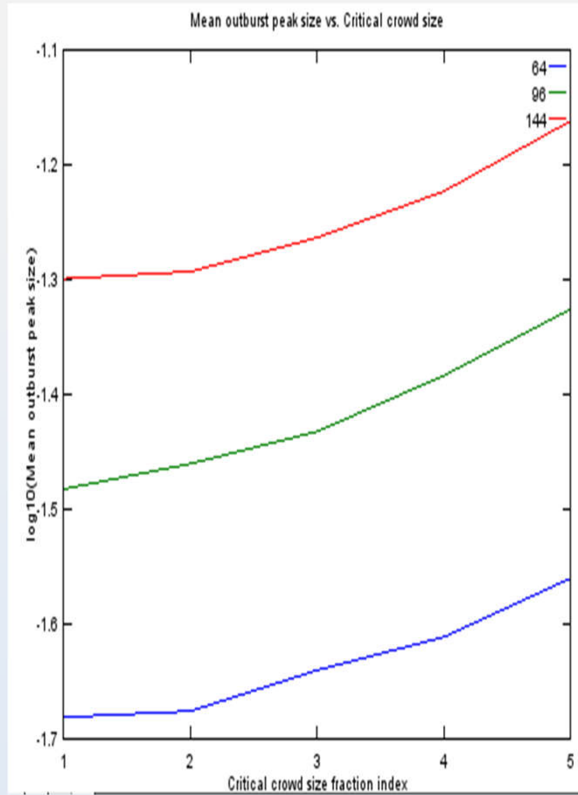


Decrease!?

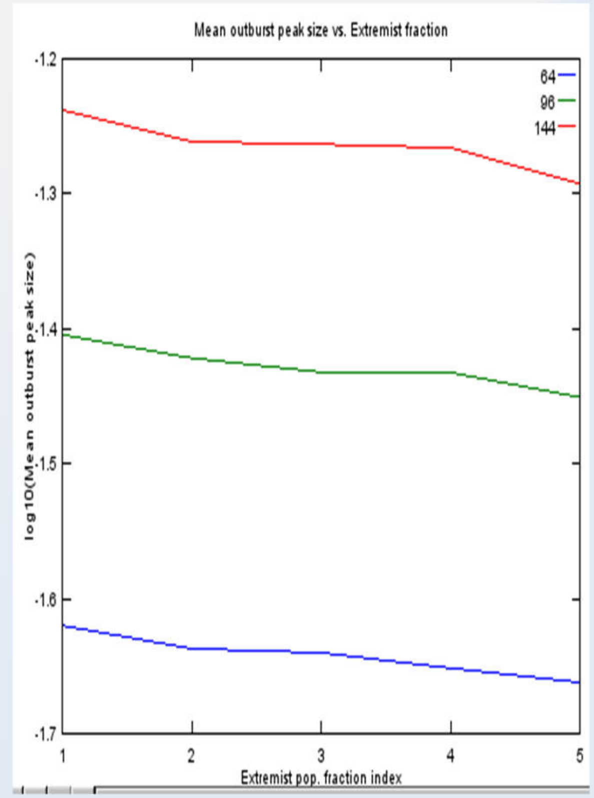
(log of) Outburst peak size



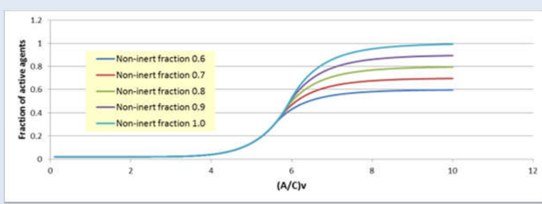
Excitables



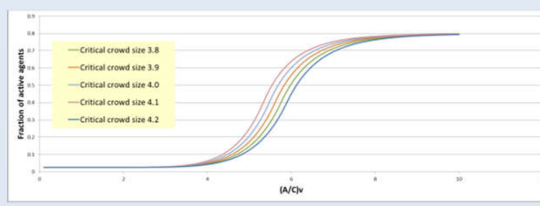
Critical crowd side



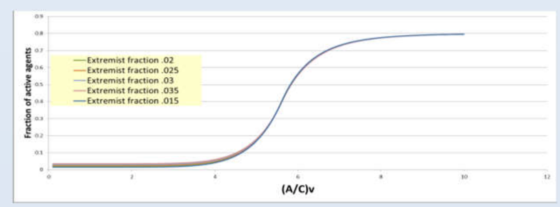
Hotheads



Goes through the roof

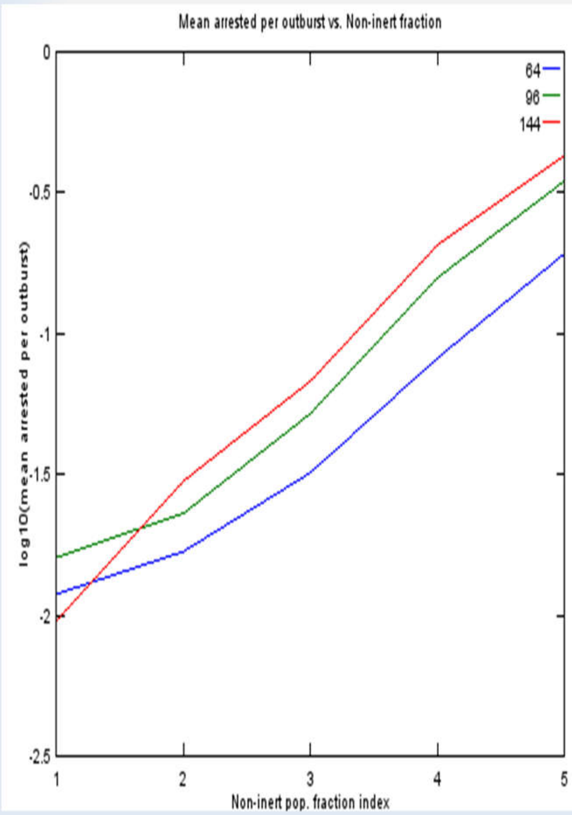


Steady increase

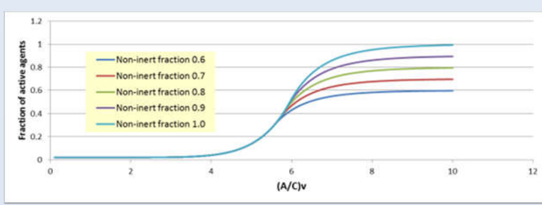


Decrease!?

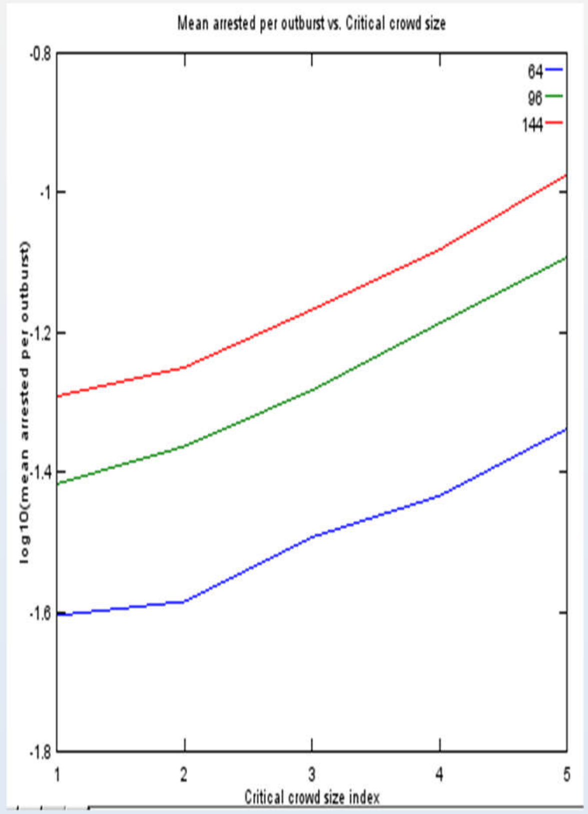
(log$_{10}$ of) Total number of arrests



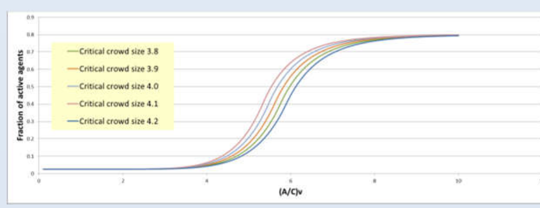
Excitables



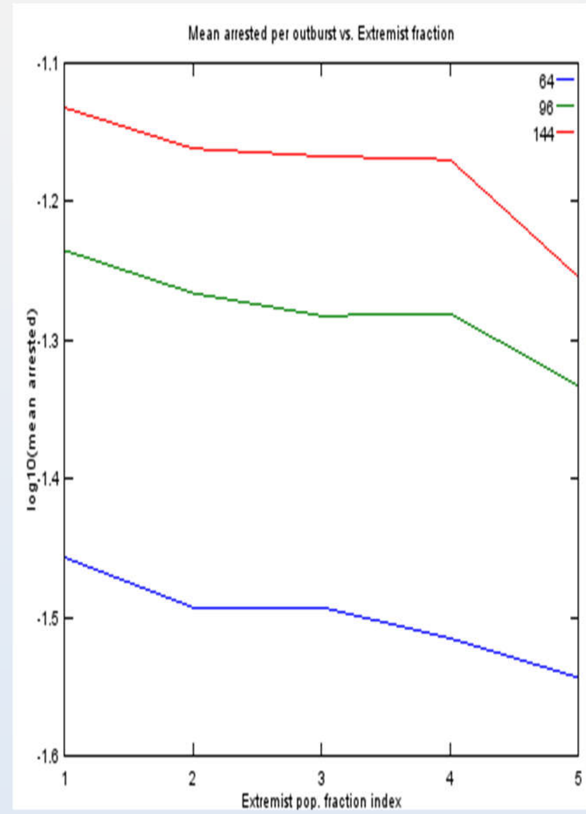
Steady increase



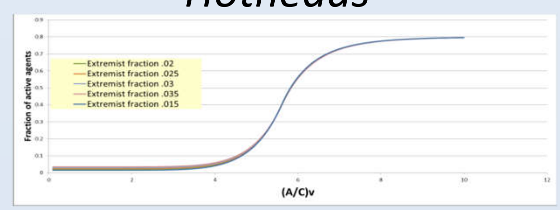
Critical crowd side



Steady increase

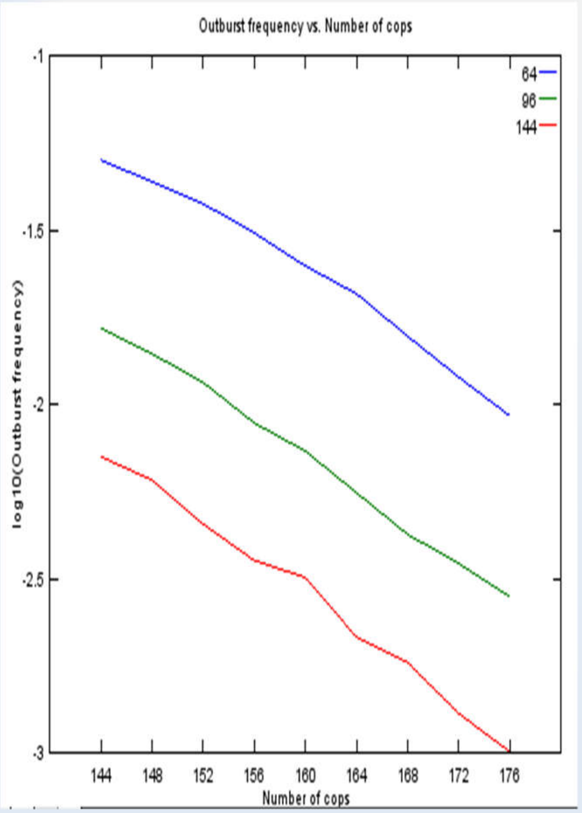


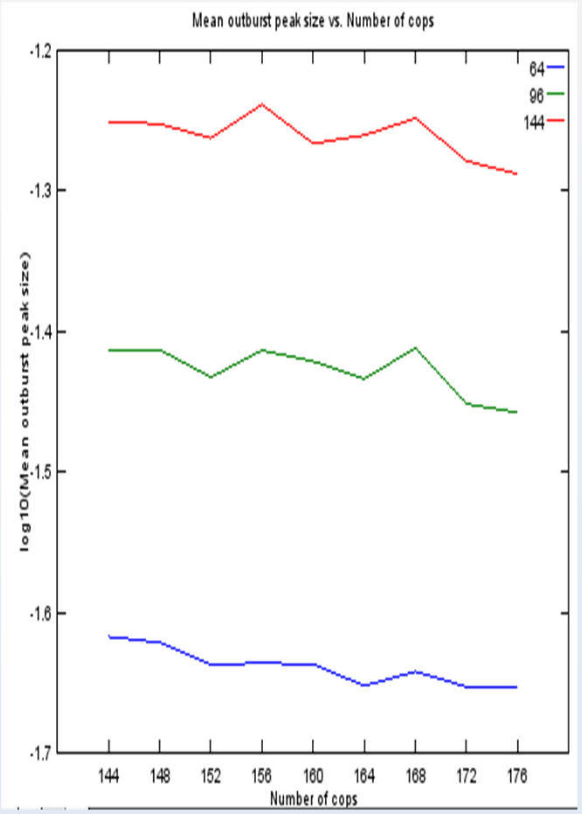
Hotheads

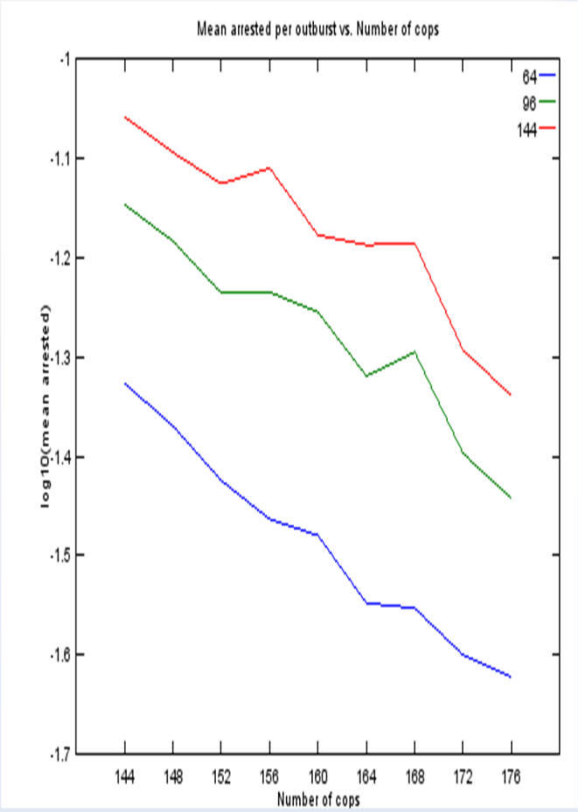


Decrease!?

Increase the "police force"?







Frequency goes down rapidly

Size is stable

Arrests decrease slightly

Caveats and limitations

- How do you obtain the model parameters from sociological data?
  - “Hardship”? “Legitimacy”? “Threshold”?
- In fact, **model parameters are proxies for complicated social effects**:
  - *Riots don’t start simply because cops are not there*
  - *Violence is suppressed by reasons other than agents are in jail.*
  - *Models of “grievance” are highly simplistic, not supported by studies*

Final Assessment

The model gives some generic insights

- It gives a plausible explanation of observed outburst sizes and waiting times
- The model provides some guidance in situations where the past history is known
- The model can inform some policy decisions in planning to prevent/control violent outbursts

***But* the devil's in the details**

- The model's parameters have no direct interpretation
- "Artifacts" in the model lead to unrealistic details
- The model is a 'sketch' and not a detailed picture. *It should not be taken too seriously.*

Modeling South African Service Protests using the National Operational Environment Model

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Service Protest Characteristics

- Since 2004, violent “service protests” have become increasingly common in poor townships in Gauteng Province, South Africa.
- Protests are due to latent grievance (Gov’t fails to provide basic services), triggered by relatively minor incidents
- Protests are uncoordinated & unplanned.
- Province-wide “superburst” of protests occurred March 2010
- Goal: an agent-based model that accounts for space-time distribution of protests, including the “superburst”

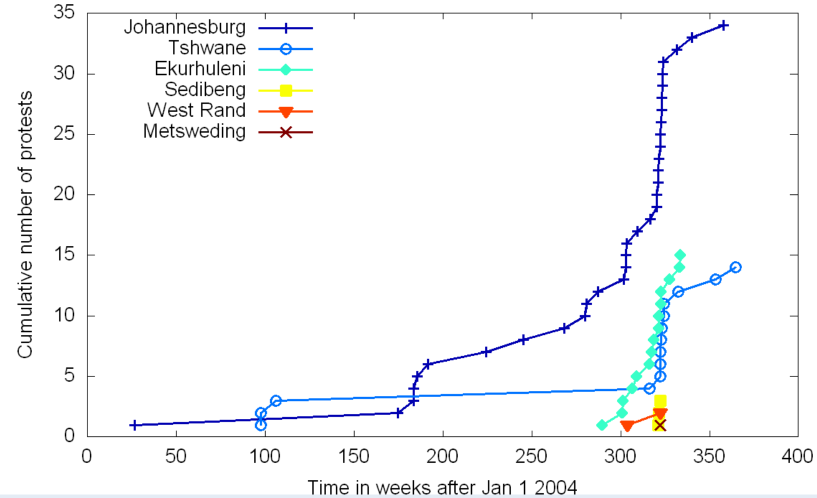
Agent-based modeling: challenges

- Protest data is only available on the township level
  - No information about individual agents and their interactions; difficult to determine their dynamics
- Non-local aspects of superburst
  - Agent-based models on a grid have local propagation of influence, and thus cannot account for the non-local superburst.
- Need a systematic (non–ad-hoc) way of determining system parameters from data
  - Necessary if the model is to have predictive value

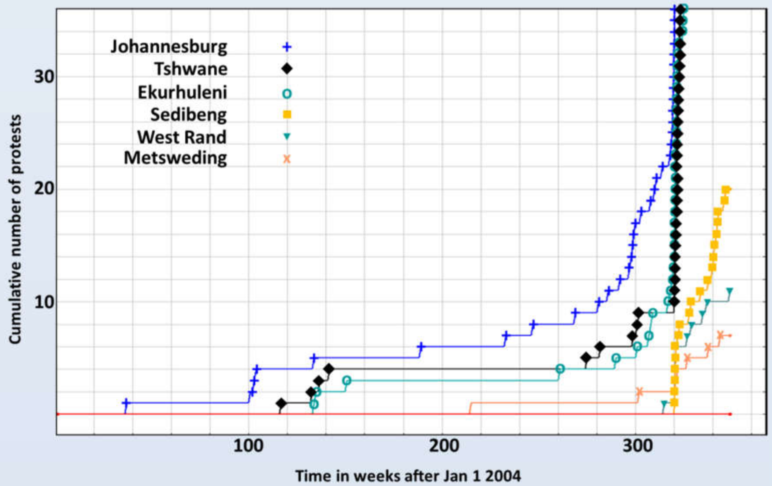
Agent-based modeling: Solutions

- Treat each township as a “super-agent”
  - Each township is modeled an agent-based “black box”, with exponential inter-protest times
- Add a non-local term to the agent-based dynamics
  - The added term reflects the province-wide level of activism
- Use earlier data to compute system parameters & trends
  - Validate parameters with later data
  - Results show good agreement with observed event distribution.
  - See the poster for details!

Cumulative distribution of protests (in time)



Actual data



Example model run

Modeling South African Service Protests using the National Operational Environment Model (NOEM)

Chris Thron (TAMU-Central Texas), John Salerno (AFRL), Adam Kwiat (CUBRC) , Philip Dexter (SUNY Binghamton), Jason Smith (ITT)

Introduction

An increasingly common worldwide phenomenon is "superbusts" of violent protests touched off by seemingly minor local events (e.g. Tunisia 12/10; Britain 08/11).

Our mathematical model of civil violence::

- Exhibits superburst phenomena.
- Can be used to assess the likelihood of a future superburst based on current data.
- Can be applied even when detailed location and size data is not available.

The model was developed and tested on one particular historical scenario, namely service protests in Gauteng Province, South Africa.

Figure 1. Service protest, Zandspruit, Gauteng Province South Africa

Social background

South African service protests are increasingly common since 2004.

- They are due to the government's inability to provide basic services
- They occur primarily in poor townships in urban areas
- They may involve looting, destruction of property, arson, blocking of roads.
- Police may use tear gas and rubber bullets against protestors.

Figure 2. Districts in Gauteng Province.

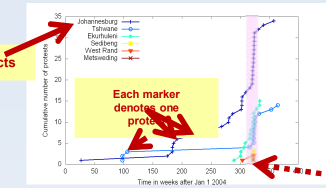


Figure 3. Cumulative time distribution of protest events, Gauteng Province 2004-10.

Agent-based modeling methodology

The NOEM behavior model is based on Epstein's agent-based model of civil violence [1].

- Agents correspond to a groups of individuals in the population;
- Agent's status reflect the group's overall level of violence (active, inactive, or "jailed").
- At each time step, each non-jailed agent chooses whether or not to be active based on the agent's perceived "grievance" (G) and "net risk" (N) according to the criterion:

$$G - N > \text{Threshold.}$$

- Law enforcement is represented by "cop" agents that patrol the grid and jail active agents within their "vision". A jailed agent remains inactive for a random period up to a maximum jail term.
- An agent's net risk N depends on the number of cops and actives within its vision.

Model adaptations

1. Townships are treated both as agent-based "black box" subsystems *and* as "superagents".

- Mathematical results from [2] justify using exponentially-distributed inter-protest times in each township under constant conditions.
- Township protests influenced neighboring townships via the agent-based dynamics described above.

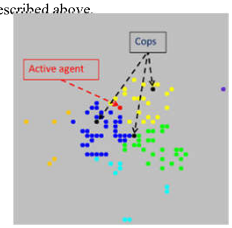


Figure 4. Example "superagent" configuration (one "superagent" = one township)..

2. To account for long-range influence of other protests, we revised the legitimacy:

$$L_{revised} = L_{basic} - K(\#Activists / \#Populace)$$

Parameter estimation

We developed a systematic methodology for data-driven parameter fitting.

Time step was set = 1 week, corresponding to agent "memory" of prior protests

The threshold, legitimacies, and legitimacy decrease were found via a system of equations based on pre-outburst per-district protest frequency data.

Maximum jail term, agent vision, and cop vision were set based on statistical analysis of protest space-time correlations.

The long-range activism parameter was chosen so as to account for the discrepancy between protest frequency during the

Table 1. Model parameters used in NOEM simulation

Parameter	*Value*
Number of agents (townships)	100
Number of cop agents	3
Size of grid (in km & cells)	270 & 50
Populace vision & cop vision (in km)	10 & 25
Hardship H (all districts)	0.5
Legitimacy L (by district)	0.8(Joh),0.83 (Tsh),0.85(Ek) 0.87(other)
Legitimacy decrease per time step δ	0.00037
Activism-determining threshold T	0.366
Agent grievance standard deviation σ	0.0
Maximum jail term J (in time steps)	25
Long-range activism constant K	6.3

85

Decreasing legitimacy ⇒ Increasing grievance

Simulation results

Randomized simulation results vary from run to run, but in general the cumulative protest distributions strongly resemble the observed cumulative distributions (see Figure 5).

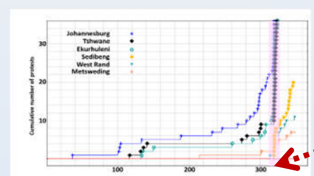


Figure 5. Cumulative time distribution of protest events (results from one simulation).

Table 2 compares data and simulation via the following statistics, which are potential indicators of future superburst likelihood:

- # isolated protests preceding the superburst, (no other protest occurs during the same, prior, and following time steps.)
- Superburst time: time step during which the maximum number of protests was observed.
- Precursor interval: # time steps prior to the superburst time during which at least one protest occurred per time step;
- # pre-superburst protests: total number of protests up until the beginning of the precursor interval.

Highly variable protest statistics

All observed values are within the simulation range

Table 2. Comparison of simulation results with Gauteng Province data

	# isolated protests	Superburst time (weeks)	Precursor interval (weeks)	#pre-superburst protests
Simulation	9.4±6.6	[illegible]±70	6.2±5	20.7±19
Observed	[illegible]	[illegible]	[illegible]	[illegible]

Table 3 shows the effect of roughly 10% variation in key model parameters. Precursor interval and number of isolated protests remain relatively stable under parameter change.

Table 3. Effect of parameter changes on simulation averages

Parameter change	*# isolated protests*	*Superburst time (weeks)*	*Precursor interval (weeks)*	*#pre-superburst protests*
Baseline	9.4±2.2	269±23	6.2±1.7	20.7±6.3
J:25→30	8.4±2.2	281±49	4.2±0.8	26.2±13
K: 6.3→7	7.8±2.9	268±36	4.6±1.5	30±16.7
T:0.366→0.4	11.8±0.8	471±47	5.6±3.2	33±15
δ:.00037→.0004	8.4±5.5	272±47	5±0.7	29±13
σ: 0.085→0.09	9±1.9	200±40	4.8±1.3	49±9.9

70% increase in superburst time with threshold change

150% increase in pre-superburst protests with variance change

Conclusions

- Simulation results agree with real data in important qualitative and quantitative respects. Variability in simulation results reflects the difficulty in predicting superbursts.
- Non-localized superbursts arise naturally from the model (unlike previous agent-based models)..
- Systematic parameter-estimation methodology can be applied to other systems.

Literature cited

1. Epstein, Joshua M., Modeling civil violence: An agent-based computational approach, PNAS, May 14, 2002; vol. 99, suppl. 3, pp. 7243-7250.
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Acknowledgments

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Modeling and Simulation of Sectarian Tensions in Split Communities

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Overview

- Many communities are divided between 2 major distinct ethnic or religious groups. (Example: Christian/Muslim or tribal divisions in central Africa.)
- The situation may or may not be accompanied by interreligious/ethnic tensions
- We propose and analyze a mathematical model of intergroup relations
- Our purpose is to identify signs of trouble, analyze stability, and to assess the effectiveness of strategies for improving relations.
- Our purpose is NOT quantitative prediction

Model Assumptions

1) Individuals within each group have varying degrees of affinity towards the other group. (Affinity is measured on a linear scale.)

2) Constructive interactions between individuals from different groups tend to improve those individuals' affinities for each other.

3) Individuals that interact predominantly within their own group tend to become increasingly negatively oriented towards and less likely to interact with the other group.

4) In interpersonal interactions, individuals tend to influence other individuals toward their own opinion.

Mathematical Formulation

- Both groups have N agents
- Each agent A has an *affinity* $a(A)$ towards the other group which takes a value between 0 (extreme hostility) to 1 (equal acceptance).
- Random sequential agent-to-agent interactions produce changes in the affinities of the interacting agents

Interaction specification (1): Choice of interaction participants

Each interaction involves 2 agents:

- Agent, A_1 is chosen randomly from either group
- Agent A_2 is chosen according to the following rule:
  - With probability, $1 - a(A_1)/2$, agent A_2 is in same group as A_1
  - If not, A_2 is chosen from other group.

***Note:* $a(A_1)=1$ implies that A_2 is chosen from either group with equal probability, while $a(A_1)=0$ implies A_2 is always in same group as A_1)

Interaction specification (2): opinion change in interacting agents

If the 2 agents are in same group:

$$a(A_1) \rightarrow a(A_1) - b_1 + c \cdot h(a(A_2) - a(A_1)) + \sigma\nu_1$$
$$a(A_2) \rightarrow a(A_2) - b_1 - c \cdot h(a(A_2) - a(A_1)) + \sigma\nu_2$$

If the 2 agents are in different groups:

$$a(A_1) \rightarrow a(A_1) + b_2 + c \cdot h(a(A_2) - a(A_1)) + \sigma\nu_1$$
$$a(A_2) \rightarrow a(A_2) + b_2 - c \cdot h(a(A_2) - a(A_1)) + \sigma\nu_2$$

Definitions

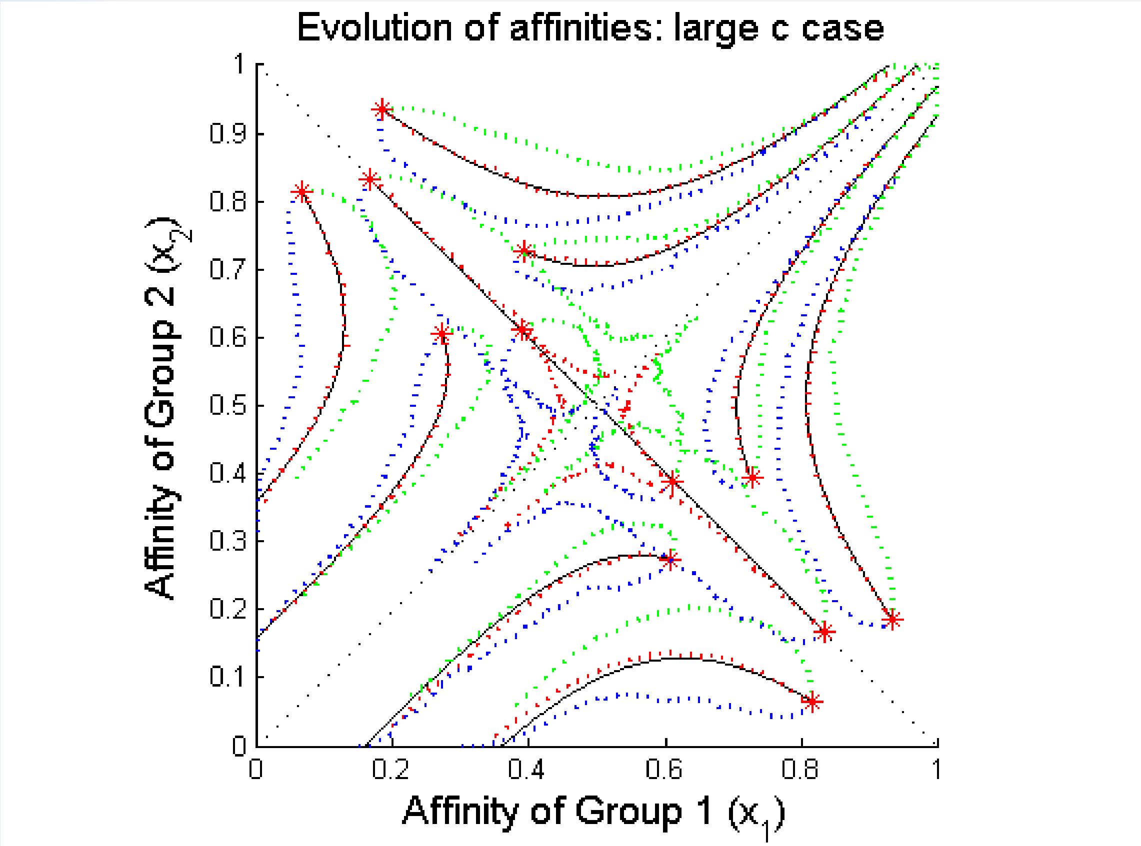
- b_1 = (negative) drift in affinity due to a single same-group interaction ($b_1 > 0$)
- b_2 = (positive) drift in affinity due to a single intergroup interaction ($b_2 > 0$)
- c = "cohesion", strength of influence of one interacting agent upon another
- h = "influence function" (possibilities include $\underline{h(x) = x}$ and $h(x) = \mathrm{sign}(x)$)
- ν_1, ν_2 are independent, identically distributed normal random variables with mean 0 and variance 1
- σ = noise standard deviation;

Theory & simulation

Case #1: All agents in each group start with same affinity (2 groups' affinities can be different)

- To simplify the theoretical analysis, we assume that a "Sticky condition" holds, namely: If all agents in a particular group start with the same affinity, then they will continue with nearly the same affinity.
- Under this condition, we are able to derive equations for the expected affinities as a function of time, depending on initial affinities of the two groups and the system parameters.

Case #1 with high cohesion: simulation + theory



* Starting affinities

--- theoretical trajectory of mean affinities

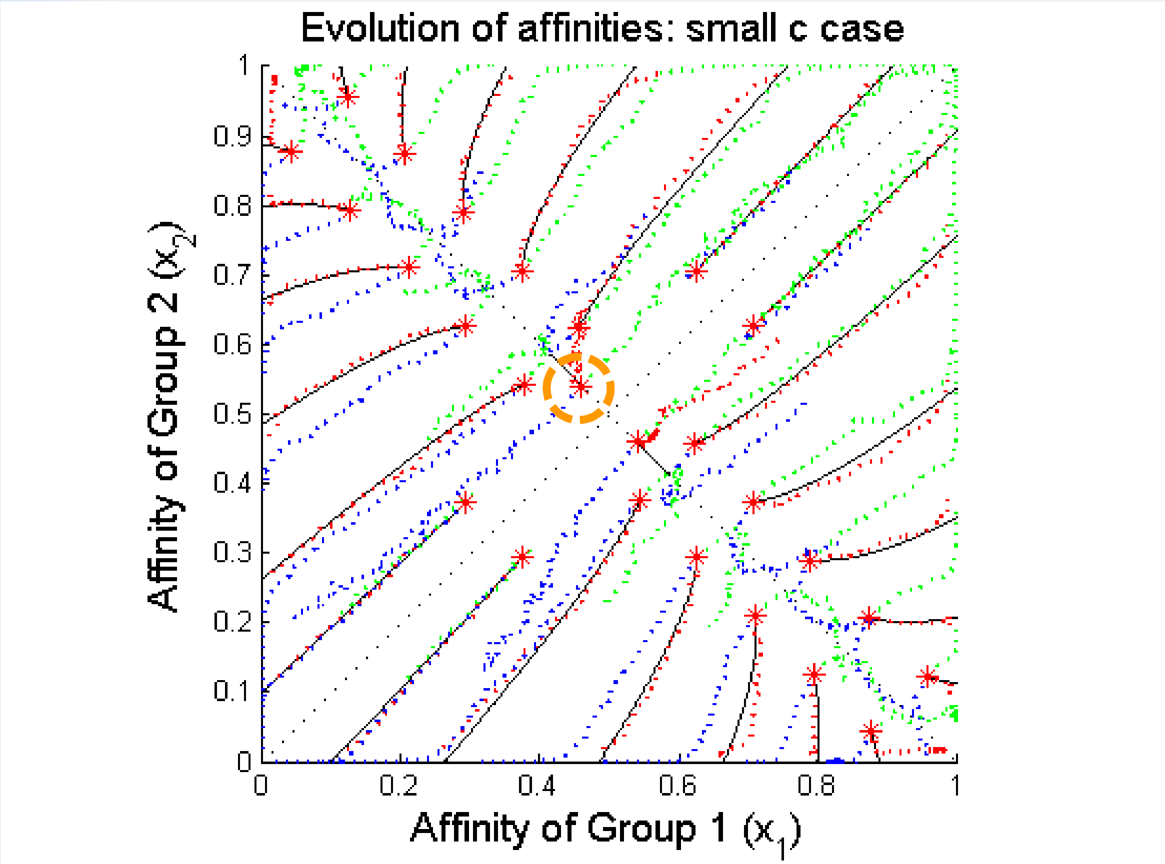
--- mean affinities trajectory (simulation)

--- 90th percentiles trajectory (simulation)

--- 10th percentiles trajectory (simulation)

- Both groups influence each other to same affinity then move together towards unanimous hostility (all affinities 0) or unanimous acceptance (all affinities 1)
- The eventual fate is extremist (resp. moderate) if the initial affinity pair (x_1,x_2) is above (resp. below) the line $x_1+ x_2 = 4/(1+ b_2/b_1)$.
- A large value of c means that there is a strong tendency to unanimity, both within and between groups.

Case #1 with low cohesion: simulation + theory



* Starting affinities

___ theoretical trajectory

----- mean affinities trajectory (sim)

----- 90th percentiles trajectory (sim)

----- 10th percentiles trajectory (sim)

- One of the two groups first reaches 0 or 1, and then drags the other group along
- The eventual fate depends solely on whether initial affinities are above/below line $x_1+x_2=4/(1+b_2/b_1)$.
- If the initial position lies exactly on this line in the small c case is it possible for groups to split into extremist and moderate factions (see circle)

Theory & Simultion

Case #2: Both groups are initially divided into extremist (affinity = 0) and moderate (affinity=1) factions.

- We consider the conditions under which such polarized groups can remain stable
- The analysis is similar to Case #1, except that each group is initially divided into extremist and moderate subgroups (four dynamical variables instead of two)

Case #2 Simulation

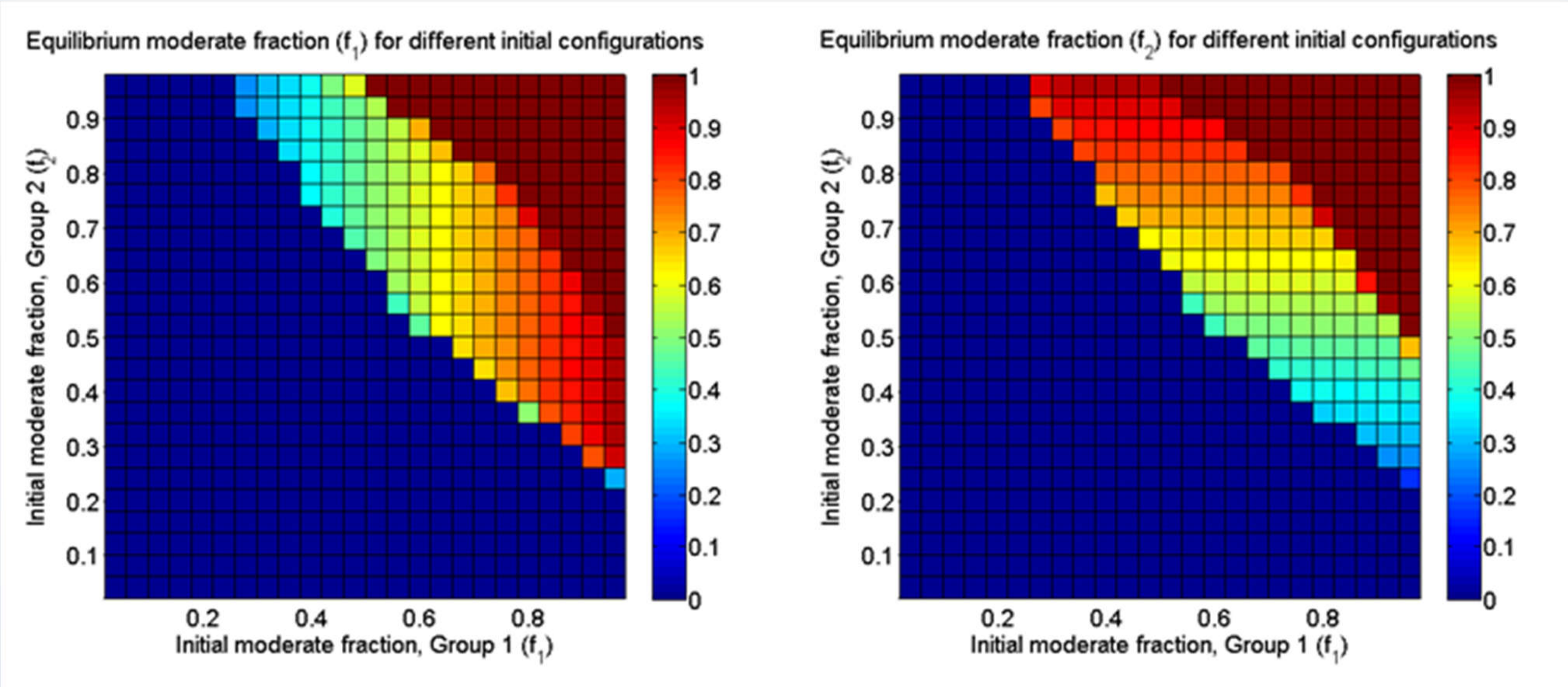


Figure 5 Equilibrium moderate fractions for Group 1 (*left*) and Group 2 (*right*) as a function of starting (Group 1, Group 2) moderate fractions in Case 2. The equilibrium moderate fractions are indicated by the color scales at right.

Community Outreach Programs

- These are programs designed to promote positive contact between individuals in the two different groups
- Include religious organizations, sports programs, etc.
- Events are assumed to occur randomly at a given frequency
- The positive effect on participants' affinities is set at the same value as the negative drift from within-group interactions
- Equal percentages of each group's population participate.
- The same individuals participate repeatedly

Community Outreach Simulation

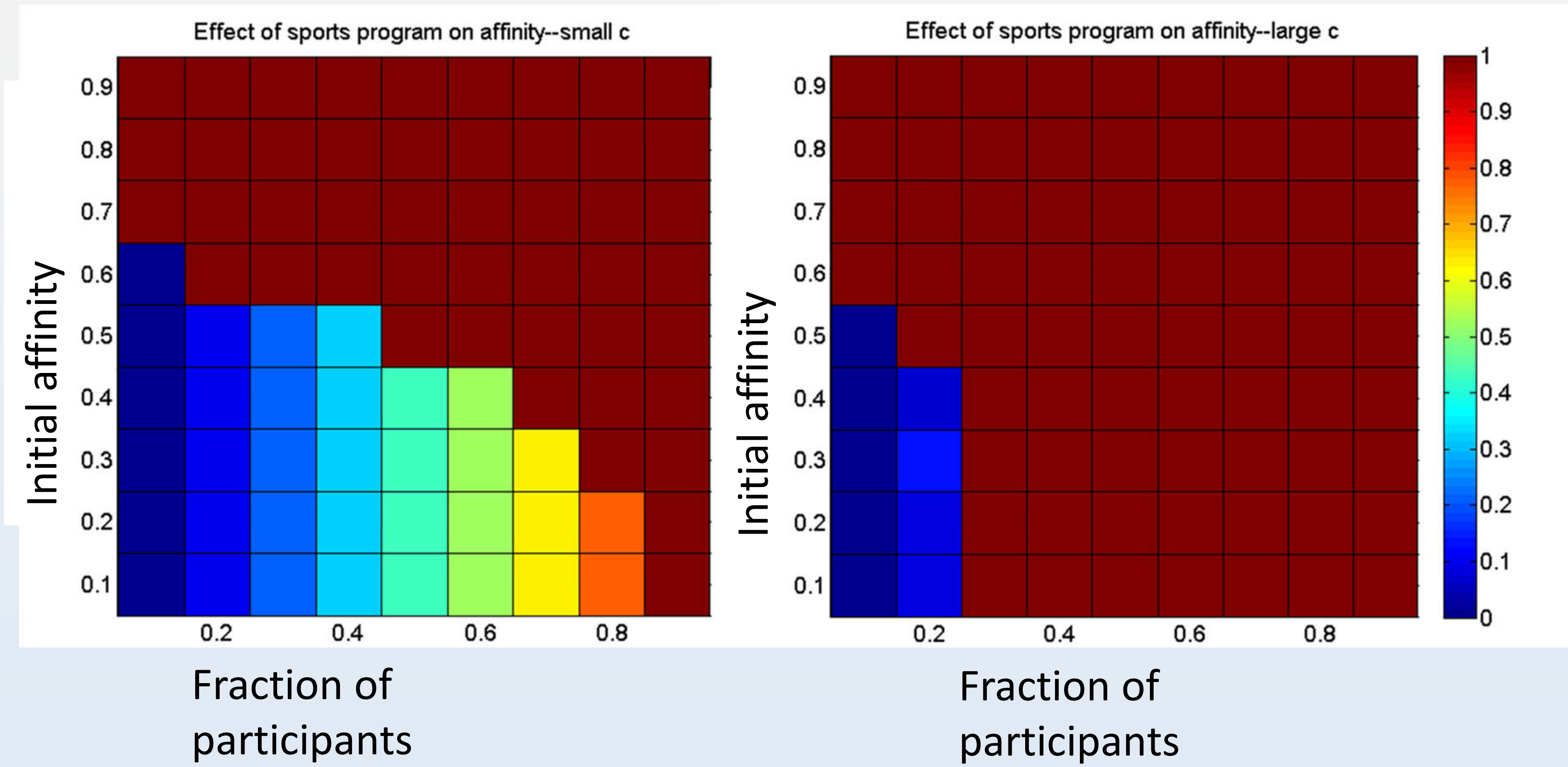


Figure 2 Equilibrium proportions of moderates (affinity > 0.9) for communities with simulated sports programs for $c= b_1/3$ ***(left)*** **and** $c=3b_1$ ***(right).***

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Discussion and Conclusion

- The ratio of positive between-group drift to negative within-group drift (b_2/b_1) is critical in determining the final fate of the system
- Effective interventions should focus on reducing b_1 and increasing b_2.
  - Reduce b_1: Actively oppose separatist tendencies and propaganda
  - Increase b_2: promote mutual educational, economic, cultural and/or social advantages derived from intergroup interactions.
- In many (but not all) cases there is a threshold of effective intervention
  - below threshold- situation will progressively deteriorate
  - above threshold- situation will eventually achieve universal moderation.
- Early intervention is required
  - larger changes in b_1 and b_2 are required to reverse trends as populations become more extreme.

Slide 44

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h47 I don't have time to look over the "discussion and conclusion" section in detail, but it needs some work. Please look over again, and we can discuss.

home, 6/14/2016

Discussion and Conclusion

- It's possible for each group to have stable moderate and extremist factions.
  - A very slight change in conditions can upset the stability either positively or negatively
- Communities in which cohesion is weakened:
  - are vulnerable to polarization
  - are much more difficult to reach through community outreach programs that target only a portion of the population.
- Simulations indicate the effectiveness of community outreaches when relationships between groups have not seriously degenerated.
  - If animosity is already strong, community outreaches may actually worsen the situation by isolating participants from their own community.
- Increasing extremism may be related to reduced social cohesion within groups due to modernization (cf. "Bowling Alone", by Robert Putnam).

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Individual Lifestyle Tradeoffs and the Decline of Society's Overall Well-being:

An Agent-based Model

(Journal of Artificial Societies and Social Simulation 19 (2) 2016)

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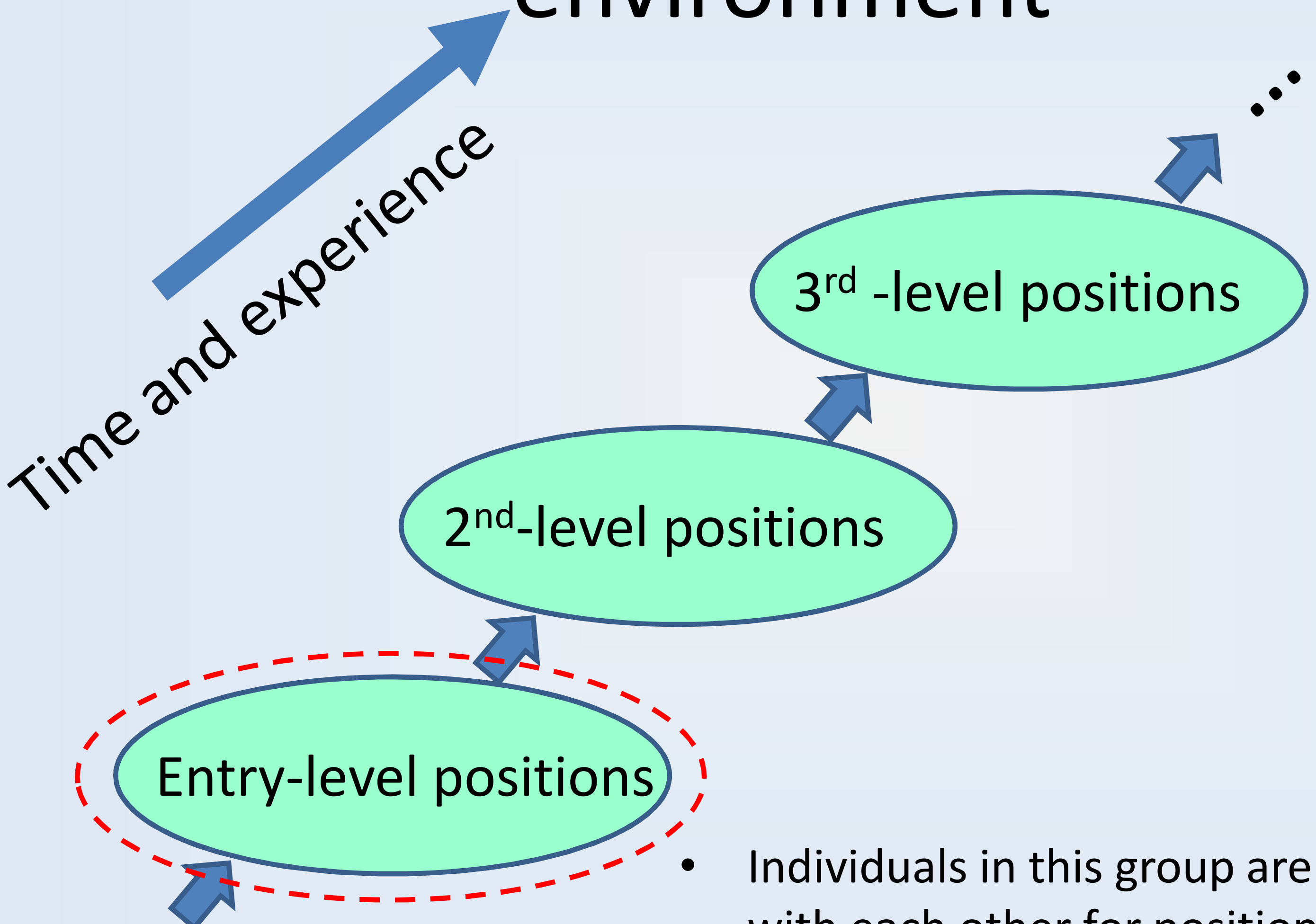
Overview

- In developed and developing societies, increases in prosperity are often accompanied by *decreases* in (self-reported) happiness.
- Can we develop a conceptual mathematical understanding of this phenomenon?
- We use *agent-based modeling* to develop a mathematical model.

A simplified model of the work environment



- Individuals in this group are in competition with each other for positions
- The current model applies to a single group

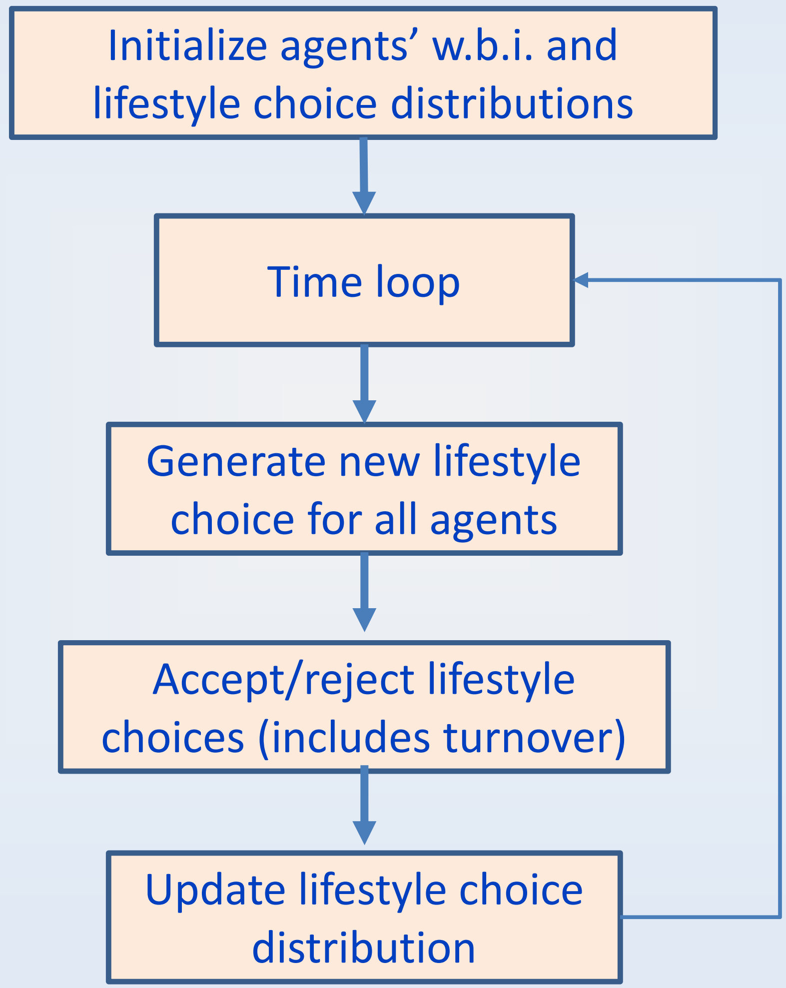
4 assumptions about behavior

A. Individuals try to maximize their own well-being
B. An individual's well-being includes both *outward* and *inward* factors.
   - Outward factors: wealth and reputation
   - Inward factors: stress, relationships, fulfillment, environment
C. Available lifestyle choices tend to reflect *outward* conditions
   - Job offers give competitive salary and benefits
   - Market value of houses are based on outward factors
D. Lifestyle choices for individuals involve *trade-offs*
   - Choices which improve one's outward situation tend to involve inward costs (e.g. stress, relocation,…)

Brief description of agent-based model

A. Individuals in the system are modeled as *agents*, where each agent has an outward well-being index (w.b.i.) and an inward w.b.i.
B. Agents randomly enter/leave the system, but the number of agents remains stable
C. As time progresses, agents are offered new lifestyle choices:
   - New lifestyle choices' mean outward w.b.i. matches the population's current mean outward w.b.i.
   - New lifestyle choices' mean outward and inward w.b.i. are negatively correlated (reflects tradeoffs).

Simulation flowchart

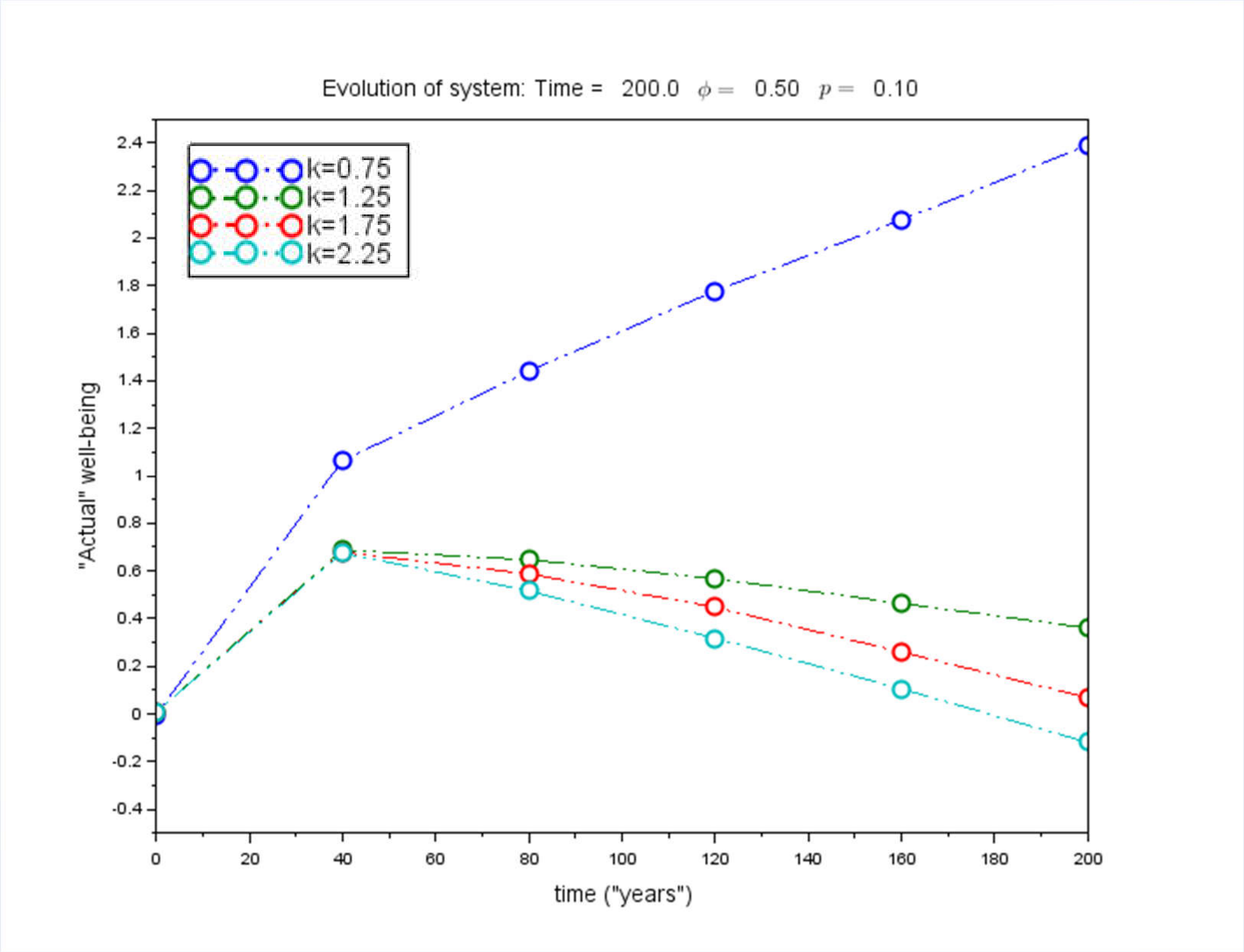


Simulation code: time loop

```
for t = 1:1:T
    // Generation of new lifestyle choices' well-being indices
    w = Mx*rand(2,N,"normal");
    w(1,:) = w(1,:)+MuW(1); // Material w.b.i.
    w(2,:) = w(2,:)-k*MuW(1); // Inward w.b.i. (negative corr.)
     // Agents accept choices which improve their net well-being
    criteria = (w(2,:) + w(1,:) > W(2,:) + W(1,:));
    // Add turnover probability and choice rate
    criteria=((criteria+ ...
            (1-criteria).*(rand(1,N,"uniform")<p))).*(rand(1,N,"uniform")<f);
    // Adjust agents' index values
    diffW = w-W;
    W(1,:) = W(1,:)+ criteria.*diffW(1,:);
    W(2,:) = W(2,:) + criteria.*diffW(2,:);
    // Adjust  lifestyle choice distribution
    MuW = mean(W,2);
  end
```

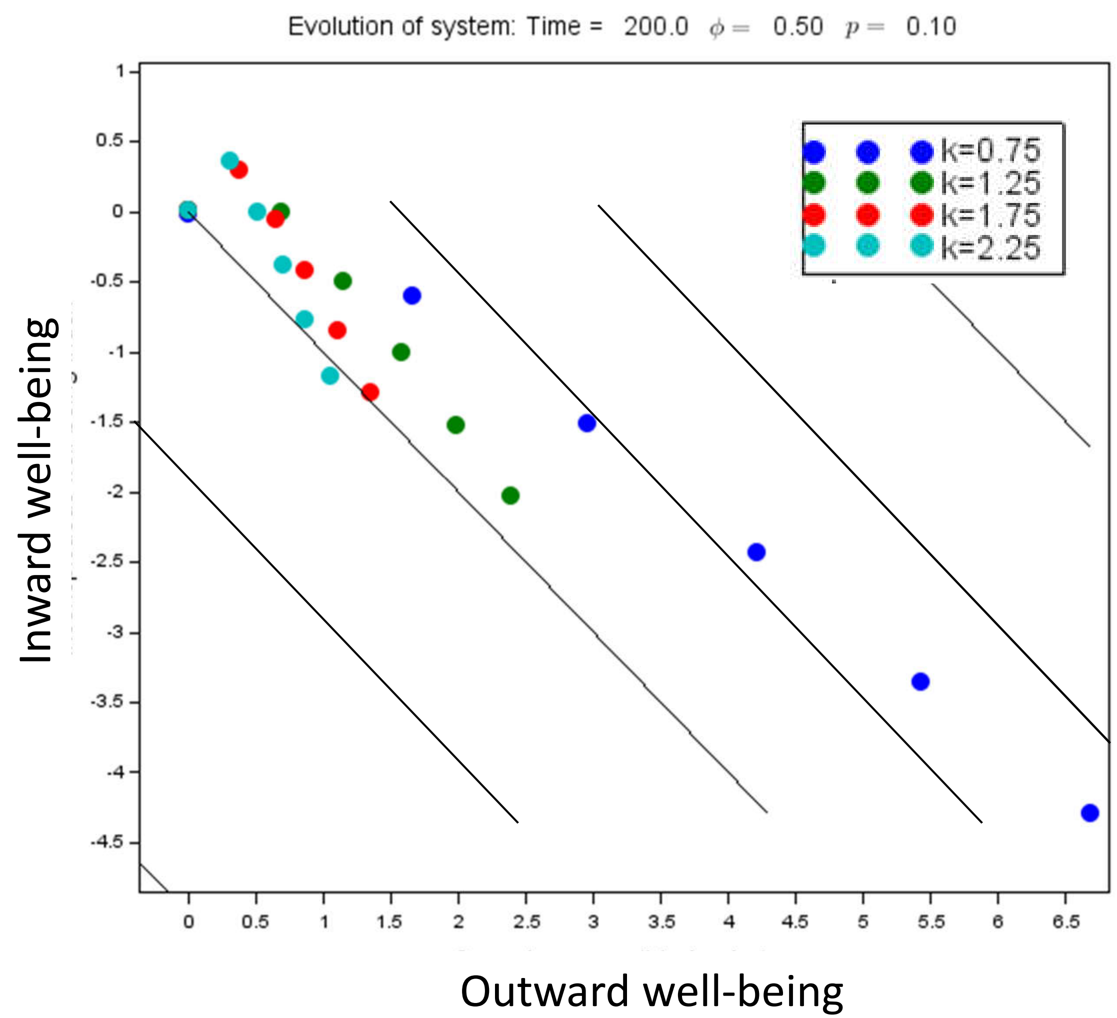
Simulation results

- Graph shows change of mean population well-being over time
- Results are shown for different conspicuous-inconspicuous tradeoff rates
- Well-being decreases whenever tradeoff rate is greater than 1



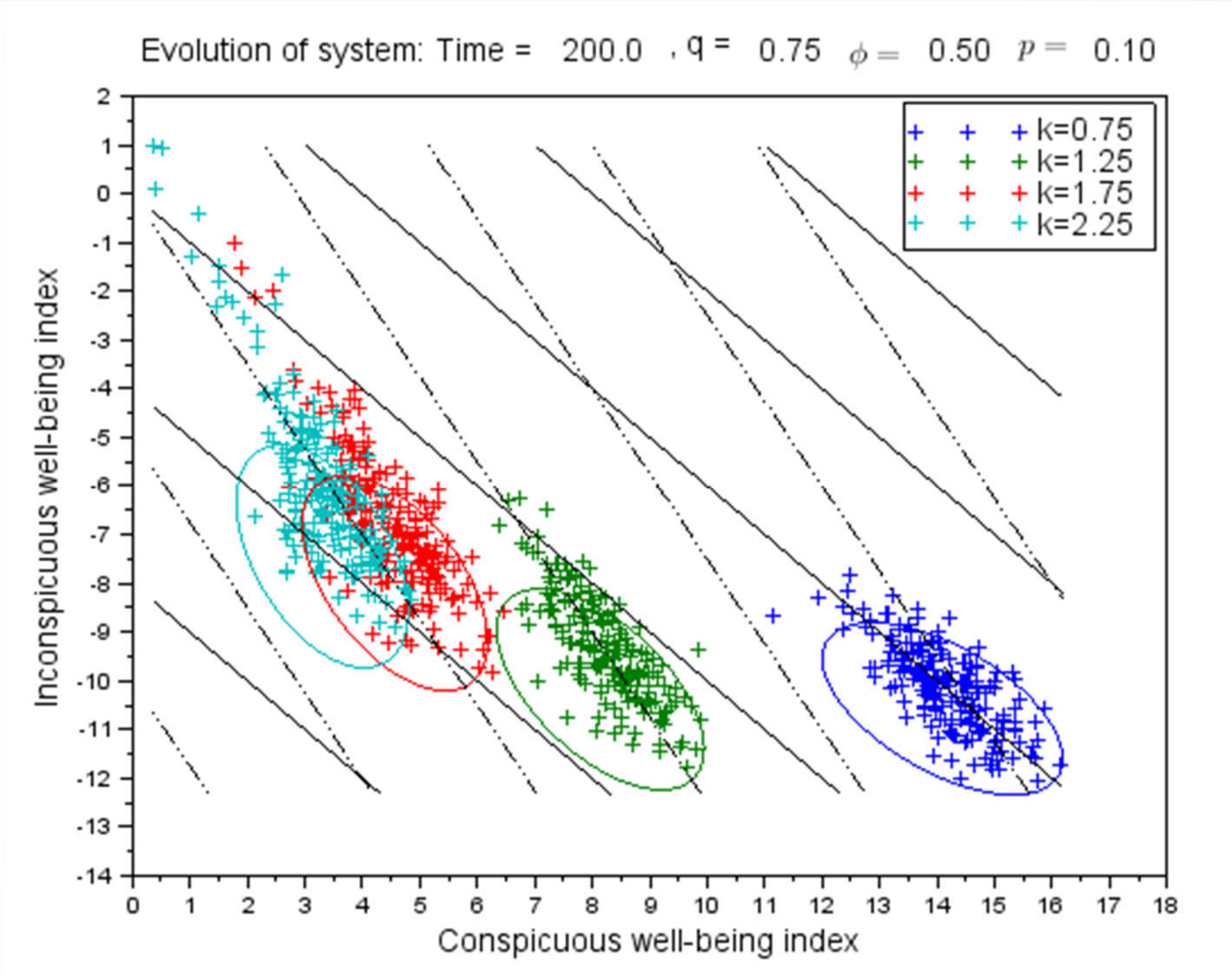
Simulation results (1)

- Solid lines are lines of constant well-being
- All scenarios start at (0,0)
- Temporary increase, followed by steady decrease.



Simulation results (ctd)

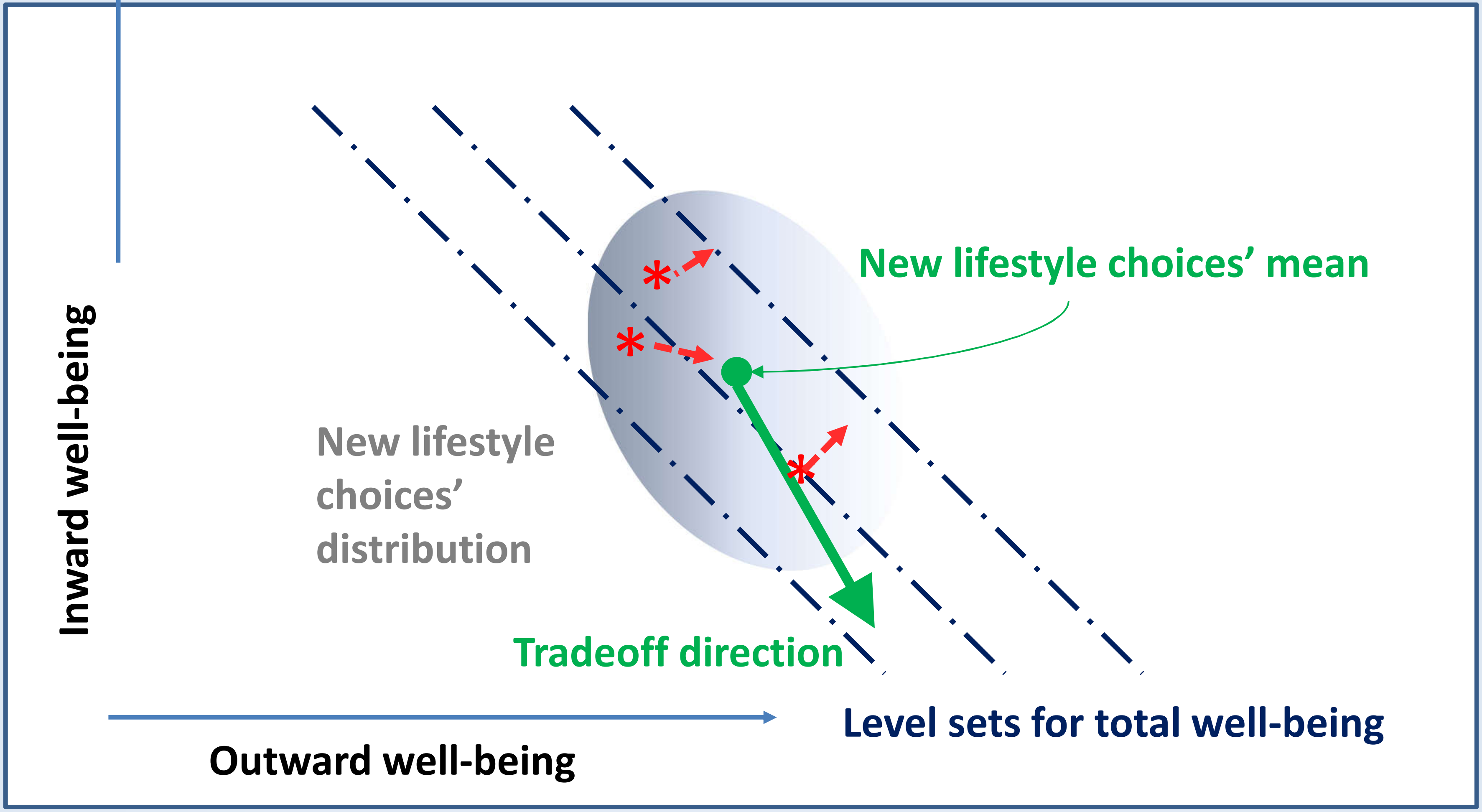
- Same results as last slide, showing agent distributions at time T = 200.
- Solid lines are lines of constant well-being
- Colored ellipses are covariance ellipses for new lifestyle choices.
- All scenarios start at (0,0)
- Actual well-being *decreases* when the tradeoff factor >1



Why does the system behave like this?

- Agents tend to want positions that improve their outward well-being
- This increases the average outward well-being of the system
- This increases the average outward well-being of new lifestyle choices
- Because of trade-offs, this decreases the average inward well-being of new lifestyle choices
- If the trade-off between outward and inward well-being is unfavorable, then new choices have lower average overall well-being
- New agents coming into the system have worse choices than their predecessors.

Why does the system behave like this?



New agents choose to improve their outward well-being, which drives the society average along the tradeoff direction, making new choices worse.

Conclusions

- ❖ When available lifestyle choices (employment, purchases) are determined primarily by material norms, then economic pressures will drive outward prosperity upwards at the expense of inward aspects of personal well-being.
- ❖ If the tradeoff is unfavorable, then overall well-being is progressively worsened.
- ❖ To counteract, non-market intervention is required
  - ➢ Promote awareness through media' social/cultural/spiritual channels
  - ➢ Government regulation (employment laws)

This is nothing new…

And I saw that all toil and all achievement spring from one person's envy of another. This too is meaningless, a chasing after the wind.
(Ecclesiastes 4:4)