Addressing the validation problem for social simulations: the Adversarial Scheduling Approach

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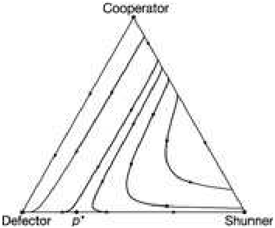
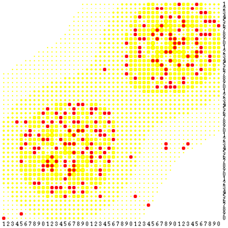
Two sides of the same coin





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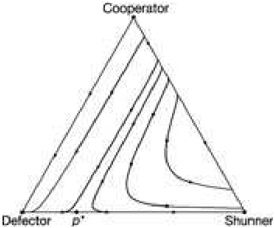

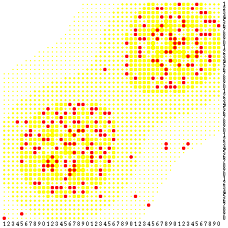

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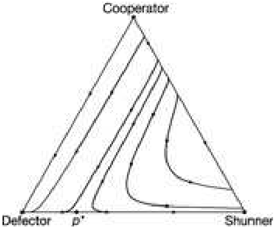

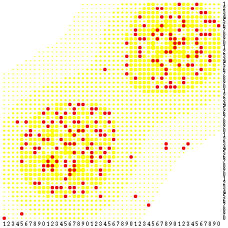

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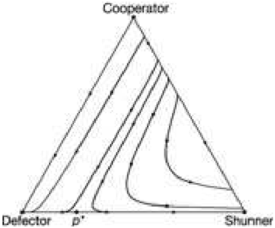

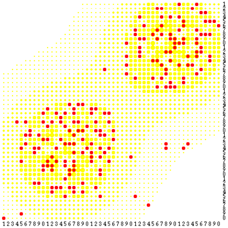

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- Agents located at the vertices of a graph.
- They have a state.
- They update the state based on social (network) interaction. Game-theoretic.

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- Peyton-Young: adding continuous noise to best-response dynamics can select (risk dominant) equilibria.

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- Want something more principled.

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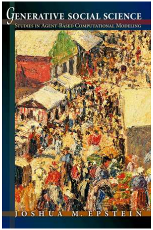

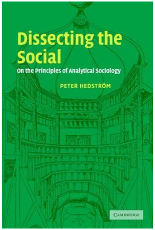

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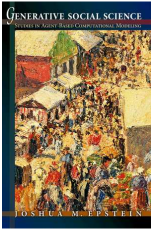

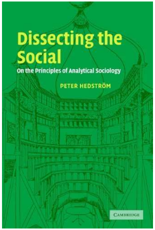

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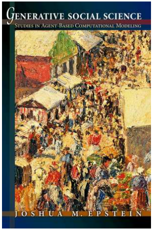

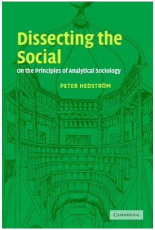

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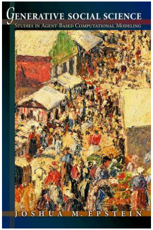

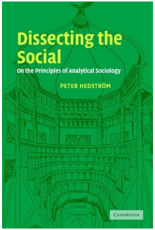

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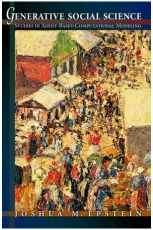

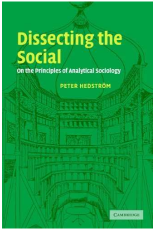

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- Formal logic in social science: not that popular. Temporal logic (Elster), logic in organization theory (Péli, Hannan).

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- Provides insight on ingredients of mechanism-based explanations.

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- Second stylized fact: *covering law*. Mapping from one domain (balls and bins) to agents.

n balls $n\ln(n) + cn$ bins random(S)	$\Rightarrow$	n agents $n\ln(n) + cn$ time steps random(S)
Pr[nonempty]$\sim 1 - e^{-e^{-c}}$		Pr[state **A**]$\sim 1 - e^{-e^{-c}}$

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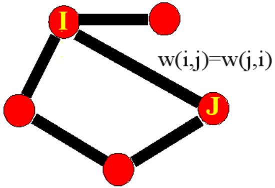
- Scheduling effectively introduces coupling in the system.

Third version: adding interaction



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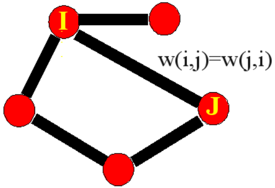

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- *A* is a *risk-dominant* equilibrium.
- $p^{\beta}(x_i \to z|\overline{x}) \sim e^{\beta \cdot \nu_i(z,\overline{x}_{-i})}$, where $\nu_i(z,\overline{x}_{-i})$, the payoff of the i'th agent should he play strategy z while the others' profile remains the same is given by $\nu_i(z,\overline{x}_{-i}) = \sum_{(i,j)\in E} w_{ij} m_{z,x_j}$.

Peyton-Young's result

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- Theorem (P.Y.) Under **random scheduling A** only stochastically stable state.

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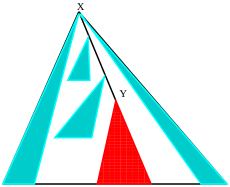
- Generalizes random scheduler (random walk on the complete graph).
- Markov chain on state space $V^{\{A,B\}} \times V$.
- **Theorem [GMR08]:** *Under RW scheduling the set $S_0 = \{(A,x) | x \in V\}$ is the set of stochastically stable states*.

Proof idea

Definition A *tree rooted at node j* is a set T of edges such that for any state $w \neq j$ there exists a unique (directed) path from w to j. The *resistance of a rooted tree T* is the sum of resistances of all edges in T.

Proposition *Let P^ϵ be a regular perturbed Markov process, and for each $\epsilon > 0$ let μ^ϵ be the unique stationary distribution of P^ϵ. Then $\lim_{\epsilon \to 0} \mu^\epsilon = \mu^0$ exists, and μ^0 is a stationary distribution of P^0. The stochastically stable states are precisely those states z such that there exists a tree rooted at z of minimal resistance (among all rooted trees).*

Proof idea (II)



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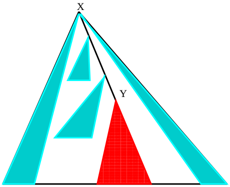

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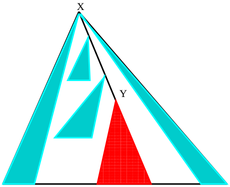

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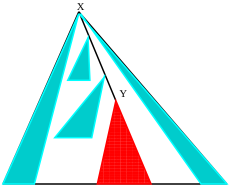

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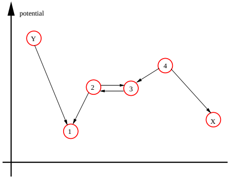

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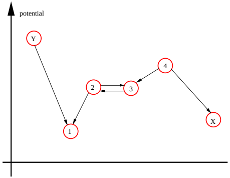

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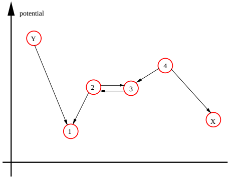

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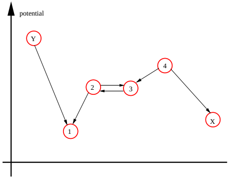
Proof idea (III)



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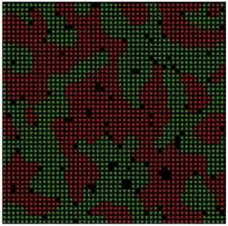
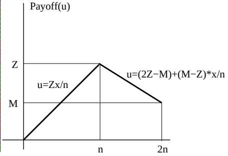
Potential game & . . .
fair(S) & nonadaptive(S) $\gg$ "$(\forall x)$ A(x) only stable state"

Application: Schelling's Segregation Model





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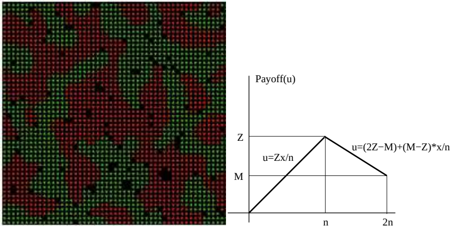

- Similar idea: *Schelling's Segregation Model.* Peyton-Young (1-D), Zhang, Pollicott& Weiss (2-D).
- Scheduler: **(Markovian contagion)** To each pair of vertices e we associate a probability distribution D_e on $V \times V$. We then choose the next scheduled pair according to the following process: If t_i is the pair scheduled at stage i, we chose t_{i+1}, the next scheduled pair, by sampling from D_{t_i}.

Application: Schelling's Segregation Model (II)

- Agents' utility function: $u_i(\cdot) = rw(\cdot) + \epsilon$, where r is a positive constant, and $w(x)$ is defined as the difference between the number of neighbours of x having the same color and the number of neighbors of x having the opposite color. Further assumptiion: same constant r, but possibly different constants ϵ.
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- Several details specific to Schelling's SM. Structure of stochastically stable states.

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where $e(S', S)$ is the number of edges with one endpoint in S' and the other in S, and $deg(i)$ is the degree of vertex i. A graph G is *(r, k)-close-knit* if every vertex is part of a r-close-knit set S, with $|S| = k$.

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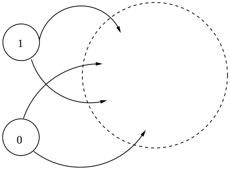
- Generalization: parameter called *Matthews bound* for Markov chains. Upper bounds on convergence time.

Extension: work in progress



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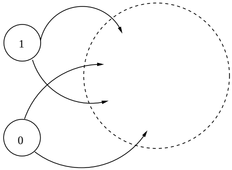

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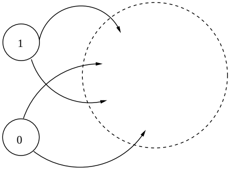

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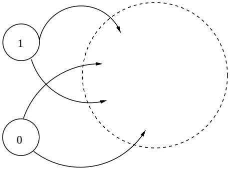

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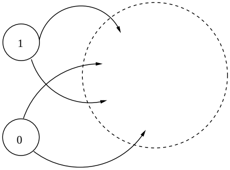

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- **Stochastic stability $\equiv$ "all A" states.**

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- Ingredient: processes as first-class objects. *Executable* specification to make model-checking/monitoring tractable.