

# Game Theoretic Learning and Social Influence

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IPAM Workshop on Decision Support for Traffic  
November 16–20, 2015

- *Traffic decision makers:*

- Users
- Fleet managers
- Infrastructure planners

*cf., Ritter: "Traffic decision support", Thursday AM*

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*Satisfaction with decision depends on decisions of others.*

- **Commuting:**
  - Decision = Path
  - Satisfaction depends on paths of others
- **Planning:**
  - Decision = Infrastructure allocation
  - Satisfaction depends on utilization



“... the study of mathematical models of conflict and cooperation between intelligent rational decision-makers”

Myerson (1991), *Game Theory*.

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- *Extensive literature...*
- *Game elements:*
  - Players/Agents/Actors
  - Actions/Strategies/Choices
  - Preferences over *joint* choices

- *Game models*
- *Influence models*

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- *Game elements:*
  - Players/Agents/Actors
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- *Solution concept:* What to expect?

- *Single decision maker:*
  - Choice set:  $x \in \mathcal{X}$
  - Utility function:  $U(x)$

$$x = \arg \max_{x' \in \mathcal{X}} U(x')$$

Linear/Convex/Semidefinite/Integer/Dynamic...Programming

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Linear/Convex/Semidefinite/Integer/Dynamic...Programming

- Good *model*?

- *Issues:*

- Complexity, randomness, incompleteness, framing...
- Furthermore...are preferences even consistent with utility function?

- *Elements*: Players, choices, and preferences over *joint* choices:

$$U_i(x) = U_i(x_i, x_{-i})$$

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## Nash Equilibrium

Everyone's choice is optimal *given* the choices of others.

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## Nash Equilibrium

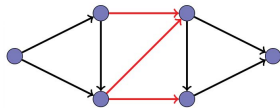
Everyone's choice is optimal *given* the choices of others.

- *Alternatives*:
  - Bounded rationality models
  - Hannan consistency, correlated equilibrium, ...

# Illustration: Congestion games (discrete)

- **Setup:**

- Players:  $1, 2, \dots, n$
- Set of resources:  $\mathcal{R} = \{r_1, \dots, r_m\}$  (roads)
- Action sets:  $\mathcal{A}_i \subset 2^{\mathcal{R}}$  (paths)
- Joint action:  $(a_1, a_2, \dots, a_n)$

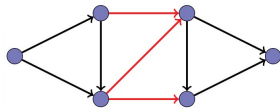




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- **Cost:** (vs Utility)

- Resource level:

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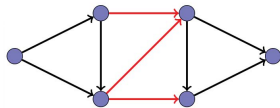
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- **Nash equilibrium:**  $a^* = (a_1^*, \dots, a_n^*)$

$$C_i(a_i^*, a_{-i}^*) \leq C_i(a'_i, a_{-i}^*)$$

- **Claim:** For such congestion games, NE minimizes

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- **Claim:** Modified resource cost

$$\phi_r(\sigma_r(a)) + \underbrace{(\sigma_r(a) - 1) \cdot (\phi_r(\sigma_r(a)) - \phi_r(\sigma_r(a) - 1))}_{\text{imposition toll}}$$

results in NE that minimizes overall congestion.

- *Discussion:*
  - Model **presumes** NE as outcome
  - How does NE compare to social planner optimal measured by  $G(\cdot)$ ?

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**pessimistic** ratio of performance at NE vs optimal performance

- *Price-of-Stability (PoS):*

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**optimistic** ratio of performance at NE vs optimal performance



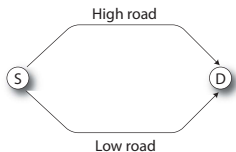
- *Setup:*

- Equally shared cost of resource:

$$\frac{\alpha}{\# \text{ users}}$$

(vs increasing congestion)

- High road:  $n - \epsilon$
- Low road: 1



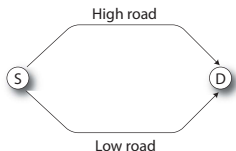
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- *NE:*
  - All use High road at individual cost  $\frac{n-\epsilon}{n} < 1$
  - All use Low road at individual cost  $\frac{1}{n}$



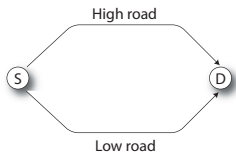
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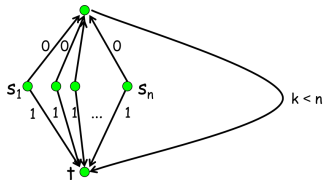
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- **PoX:**  $G(a)$  is sum of individual costs



$$\text{PoA} \approx n \ \& \ \text{PoS} = 1$$

# Illustration: Equal cost sharing, cont.

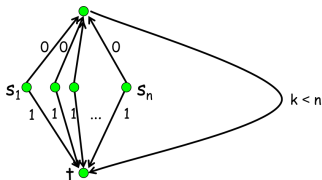
- *Setup:*
  - Equally shared cost as before
  - User specific starting points



# Illustration: Equal cost sharing, cont.

- *Setup:*

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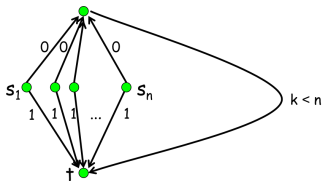


- *NE:*

- All use private resource at individual cost 1
- All use shared resource at individual cost  $\frac{k}{n}$

- *Setup:*

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- *NE:*

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- All use shared resource at individual cost  $\frac{k}{n}$

- *PoX:*  $G(a)$  is sum of individual costs

$$\text{PoA} = n/k \ \& \ \text{PoS} = 1$$

- *Extensions:* Broader solution concepts, various families of games, price-of-uncertainty, price-of-byzantine, price-of- ...

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- $(\lambda, \mu)$ -smoothness: For any two action profiles,  $a^*$  &  $a'$

$$\sum_i C_i(a_i^*, a'_{-i}) \leq \lambda \sum_i C_i(a^*) + \mu \sum_i C_i(a')$$



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- *Theorem*: Under  $(\lambda, \mu)$ -smoothness,

$$\text{PoA} \leq \frac{\lambda}{1 - \mu}$$

*Think of  $a'$  as NE and  $a^*$  as central optimum*

- *Game models*
  - Setup & equilibrium
  - Price-of-X
  
- *Influence models*
  - Equilibrium shaping

*Lingering issues:*  
Uncertain landscapes  
Equilibrium analysis

- *Marginal contribution utility:*

- Assume global objective,  $G(\cdot)$
- Define “null” action  $\emptyset$
- Set

$$U(a_i, a_{-i}) = G(a_i, a_{-i}) - G(\emptyset, a_{-i})$$

- **Claim:** PoS = 1

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- *Recall:*

$$\phi_r(\sigma_r(a)) + \overbrace{\beta}^{\text{new term}} \underbrace{(\sigma_r(a) - 1) \cdot (\phi_r(\sigma_r(a)) - \phi_r(\sigma_r(a) - 1))}_{\text{imposition toll: } \tau(a)}$$

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- *Uncertain landscape:* What if users have different  $\beta$ 's?  
*many more sources of uncertainty...*

$$\phi_r(\sigma_r(\mathbf{a})) + \overbrace{\beta}^{\text{new term}} \underbrace{(\sigma_r(\mathbf{a}) - 1) \cdot (\phi_r(\sigma_r(\mathbf{a})) - \phi_r(\sigma_r(\mathbf{a}) - 1))}_{\text{imposition toll: } \tau(\mathbf{a})}$$

- **Theorem:** As  $\kappa \rightarrow \infty$

$$\kappa \cdot (\phi_r(\sigma_r(\mathbf{a})) + \tau(\mathbf{a}))$$

leads to PoA  $\rightarrow 1$

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leads to PoA  $\rightarrow 1$

- **Extensions:** Optimal bounded tolls in special case of parallel links & affine costs.

Brown & Marden (2015), "Optimal mechanisms for robust coordination in congestion games"

Private info  $\xrightarrow{\mathcal{D}}$  Social decision

vs

Private info  $\xrightarrow{\mathcal{S}}$  Messages  $\xrightarrow{\mathcal{M}}$  Social decision

- A “mechanism”  $\mathcal{M}$  is a rule from reports to decisions.
- Mechanism  $\mathcal{M}$  induces a game in reporting strategies.
- Seek to implement  $\mathcal{D}$  as solution of game, i.e.,

$$\mathcal{D} = \mathcal{M} \circ \mathcal{S}?$$



# Standard illustration: Sealed bid/second price auctions

Private info  $\xrightarrow{\mathcal{D}}$  Social decision

vs

Private info  $\xrightarrow{\mathcal{S}}$  Messages  $\xrightarrow{\mathcal{M}}$  Social decision

- *Planner objective*: Assign item to highest private valuation
- *Agent objective*: Item value minus payment
- *Messages*: Bids
- *Social decision*:
  - Item to high bidder
  - Payment from high bidder = Second highest bid
- *Claim*: Truthful bidding is a NE.
- *Special case of broad discussion...*

Private info  $\xRightarrow{\mathcal{D}}$  Social decision

vs

Private info  $\xRightarrow{\mathcal{S}}$  Messages  $\xRightarrow{\mathcal{M}}$  Social decision

- Private info is revealed *sequentially*
- Agents do not know own valuations in advance
- Decisions based on sequential messages

- Two users:  $\{1, 2\}$
- User's need for resource is low or high:  $\theta_i \in \{L, H\}$

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- Planner objective: Fair allocation with User 2 priority
- Dynamics: Coupled state transitions according to  $4 \times 4$  matrices over set

$$\{(L, L), (H, L), (L, H), (H, H)\}$$

Private info  $\xRightarrow{\mathcal{D}}$  Social decision

vs

Private info  $\xRightarrow{\mathcal{S}}$  Messages  $\xRightarrow{\mathcal{M}}$  Social decision

- *Planner objective*: Induce truthful reporting
- *Agent objective*: Future discounted resource access minus payments

$$\sum_{t=0}^{\infty} \delta^t \left( v_i(\pi(r_1^t, \dots, r_n^t), \theta_i^t) - q_i^t(r_1^t, \dots, r_n^t) \right)$$

- *Messages*: High/Low resource need
- *Theorem*: LP computations so that truthful reporting is a NE.

Kotsalis & Shamma (2013): "Dynamic mechanism design in correlated environments"

- Optimal efficient policy: Favor Agent 2

$$\pi(L, L) = 1/2, \quad \pi(H, L) = 1, \quad \pi(L, H) = 2, \quad \pi(H, H) = 2$$

- Agent 2 can monopolize by misreporting
- Payment rule:

$$q_1(\cdot, \cdot) = 0$$

$$q_2(L, L) < 0, \quad q_2(L, H) < 0, \quad q_2(H, L) < 0$$

$$q_2(H, H) > 0$$

- Ex ante payment from agent 2 = 0



*Lingering issues:*  
Uncertain landscapes  
Equilibrium analysis

- Tuned for behavior only at specific Nash equilibrium
- Presumes agents solve coordinated (dynamic) optimization
- Presumes knowledge of full system dynamics available to all
- Neglects model mismatch

- *Game models*
  - Setup & equilibrium
  - Price-of-X
  
- *Influence models*
  - Equilibrium shaping
  - Mechanism design

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## *Shift of focus:*

- Away from equilibrium—Nash equilibrium
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- Towards how players might arrive to solution—i.e., *dynamics*

“The attainment of equilibrium requires a disequilibrium process.”

Arrow, 1987.

“The explanatory significance of the equilibrium concept depends on the underlying dynamics.”

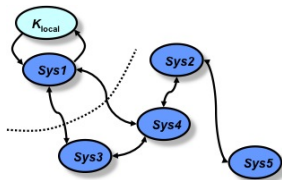
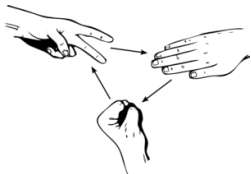
Skyrms, 1992.

### Monographs:

- Weibull, *Evolutionary Game Theory*, 1997.
- Young, *Individual Strategy and Social Structure*, 1998.
- Fudenberg & Levine, *The Theory of Learning in Games*, 1998.
- Samuelson, *Evolutionary Games and Equilibrium Selection*, 1998.
- Young, *Strategic Learning and Its Limits*, 2004.
- Sandholm, *Population Dynamics and Evolutionary Games*, 2010.

### Surveys:

- Hart, “Adaptive heuristics”, *Econometrica*, 2005.
- Fudenberg & Levine, “Learning and equilibrium”, *Annual Review of Economics*, 2009.



**Caution!** Single agent learning  $\neq$  Multiagent learning

Sato, Akiyama, & Farmer, "Chaos in a simple two-person game", PNAS, 2002.

Piliouras & JSS, "Optimization despite chaos: Convex relaxations to complete limit sets via Poincare recurrence", SODA, 2014.

$$a_i(t) \in \begin{cases} B_i(a_{-i}(t-1)) & \text{w.p. } 0 < \rho < 1 \\ a_i(t-1) & \text{w.p. } 1 - \rho \end{cases}$$

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### Features:

- Pure NE is a stationary point
- Based on greedy response to myopic forecast:

$$a_{-i}^{\text{guess}}(t) = a_{-i}(t-1)?$$

- Need *not* converge to NE



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## Theorem

For *finite-improvement-property games* under *best reply with inertia*, player strategies *converge to NE*.

(Includes anonymous congestion games...)

- *Each player:*
  - Maintain empirical frequencies (histograms) of opposing actions
  - Forecasts (incorrectly) that others play independently according to observed empirical frequencies
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- *Compare to best reply:*

$$a_{-i}^{\text{guess}}(t) = a_{-i}(t-1)?$$

vs

$$a_{-i}^{\text{guess}}(t) \sim q_{-i}(t) \in \Delta(\mathcal{A}_{-i})$$

## Theorem

For *zero-sum games (1951)*,  *$2 \times 2$  games (1961)*, *potential games (1996)*, and  *$2 \times N$  games (2003)* under *fictitious play*, player empirical frequencies *converge to NE*.

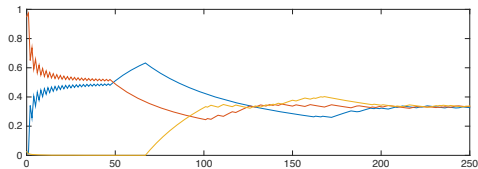
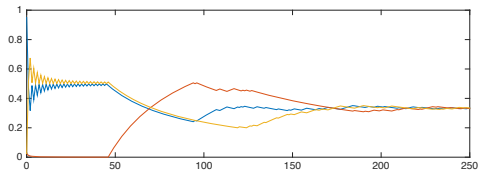
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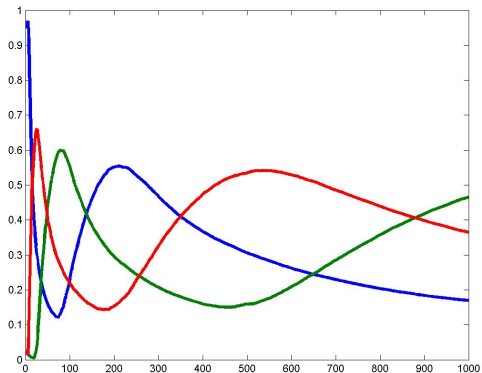
## Theorem

For *Shapley "fashion game" (1964)*, *Jordan anti-coordination game (1993)*, *Foster & Young merry-go-round game (1998)* under *fictitious play*, player empirical frequencies *DO NOT converge to NE*.

*Detail: Discussion extended to mixed/randomized NE*



*Rock-Paper-Scissors*

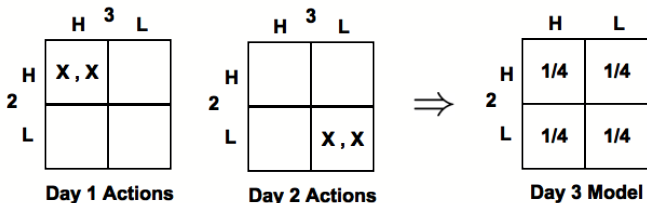


### Shapley "Fashion Game"

	<i>R</i>	<i>G</i>	<i>B</i>
<i>R</i>	0, 1	0, 0	1, 0
<i>G</i>	1, 0	0, 1	0, 0
<i>B</i>	0, 0	1, 0	0, 1

## FP bookkeeping

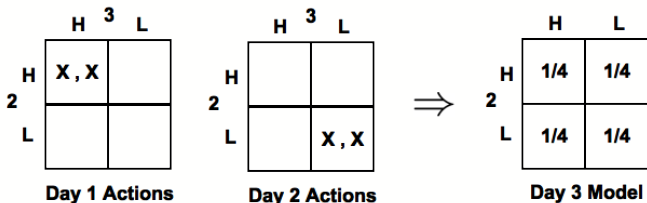
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- Construct probability distribution of **all possible** opponent configurations





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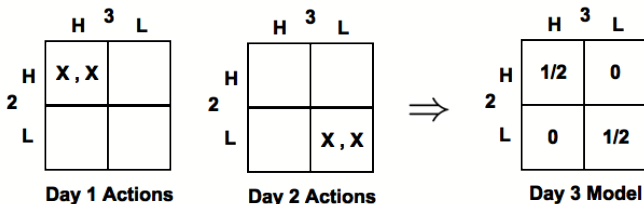
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- *Prohibitive* for large games

## Modification:

- Maintain empirical frequencies (histograms) of opposing actions
- Forecasts (incorrectly) that others play ~~independently~~ according to observed empirical frequencies
- Selects an action that maximizes expected payoff



*Virtual payoff vector*: The payoffs that **could have** been obtained

$$U_i(t) = \begin{pmatrix} u_i(1, a_{-i}(t)) \\ u_i(2, a_{-i}(t)) \\ \vdots \\ u_i(m, a_{-i}(t)) \end{pmatrix}$$

*Time averaged virtual payoff*:

$$V_i(t+1) = (1 - \rho)V_i(t) + \rho U_i(t)$$

Stepsize  $\rho$  is either *constant* (fading) or *diminishing* (averaging)

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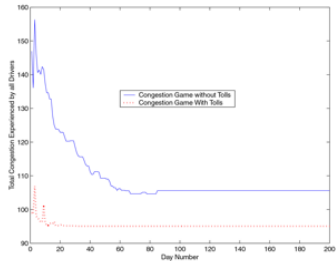
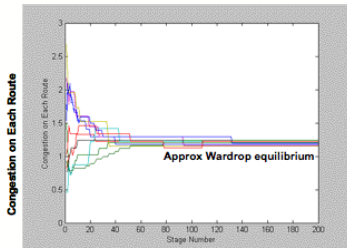
*Time averaged virtual payoff:*

$$V_i(t+1) = (1 - \rho)V_i(t) + \rho U_i(t)$$

Stepsize  $\rho$  is either *constant* (fading) or *diminishing* (averaging)

*Equivalent JSFP:* At each stage, select best virtual payoff action

*Viewpoint:* Bookkeeping is **oracle based** (cf., traffic reports)



## Anonymous congestion

- *Game models*
  - Setup & equilibrium
  - Price-of-X
  - Learning/evolutionary games
  
- *Influence models*
  - Equilibrium shaping
  - Mechanism design

*Lingering issues:*  
Uncertain landscapes  
Equilibrium analysis

- Public service advertising
  - Phase I:
    - Receptive agents: Follow planner's advice (e.g., with probability  $\alpha$ )
    - Non-receptive agents: Unilateral best-response dynamics
  - Phase II: Receptive agents may revert to best-response dynamics

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- **Main results:** Desirable bounds on resulting PoA for various settings (anonymous congestion, shared cost, set coverage...)



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- **Main results:** Desirable bounds on resulting PoA for various settings (anonymous congestion, shared cost, set coverage...)
- **Compare:** Nash equilibrium vs learning agents

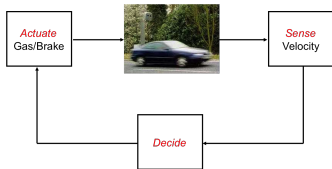
Balcan, Blum, & Mansour (2013), "Circumventing the Price of Anarchy: Leading Dynamics to Good Behavior"

Balcan, Krehbiel, Piliouras, and Shin (2012), "Minimally invasive mechanism design: Distributed covering with carefully chosen advice"

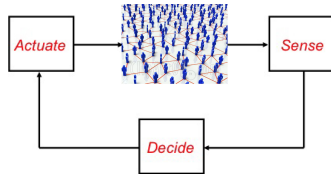
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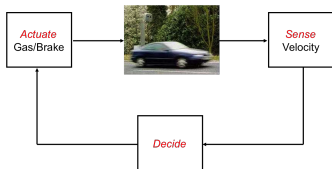
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# Social influence & feedback control

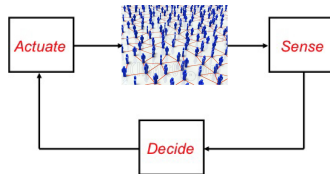


VS





VS



## Benefits of feedback (Astrom)

- Reliable behavior from unreliable **components** *humans*
- Mitigate disturbances
- Shape dynamic behavior

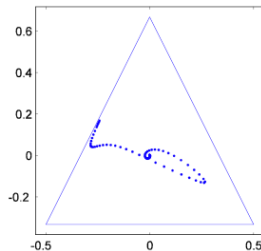
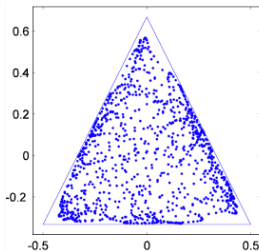
- *Modeling:*
  - Order?
  - Time-scale?
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  - Resolution?
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“Thus unless we know quite a lot about the topology of interaction and the agents’ decision-making processes, estimates of the speed of adjustment could be off by many orders of magnitude.”

Young, “Social dynamics: Theory and applications”, 2001.

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*Reinforcement learning vs Trend-based reinforcement learning*

- *Modeling:*
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  - Social network effects?
  
- *Measurement & actuation*



- *Game models*
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- *Influence models*
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- *Challenges*
  - Modeling
  - Measurement & actuation



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