

Game theory

| | | ALICE | |
|-----|---|-------|---|
| | | C | D |
| BOB | C | 3 | 2 |
| | D | 2 | 1 |

ALICE picks D

ALICE gets 2

| ALICE | | C | D |
|-------|---|---|---|
| BOB | C | 3 | 2 |
| | D | 2 | 1 |

BOB picks C

BOB gets 2

Nash equilibrium

Alice and Bob are in Nash equilibrium if Alice is making the best decision she can, taking into account Bob's decision, and Bob is making the best decision he can, taking into account Alice's decision.

| | | ALICE | |
|-----|---|-------|-----|
| | | C | D |
| BOB | C | 3 3 | 2 2 |
| | D | 2 2 | 1 1 |

Prisoner's dilemma

| | | Alice | |
|-----|---|-------|-----|
| | | C | D |
| Bob | C | 3 3 | 5 0 |
| | D | 0 5 | 1 1 |

ALICE

| | | C | D |
|-----|---|---|---|
| BOB | C | 3 | 5 |
| | D | 0 | 1 |

Diagram illustrating a game matrix with payoffs and green arrows indicating a path:

- Top row (Alice's choice C): Payoffs are 3 (if Bob chooses C) and 5 (if Bob chooses D).
- Bottom row (Alice's choice D): Payoffs are 0 (if Bob chooses C) and 1 (if Bob chooses D).
- Left column (Bob's choice C): Payoffs are 3 (if Alice chooses C) and 0 (if Alice chooses D).
- Right column (Bob's choice D): Payoffs are 5 (if Alice chooses C) and 1 (if Alice chooses D).

Green arrows indicate a path: from (C,C) to (C,D) to (D,D).

Iterated Prisoner's dilemma (IPD)

The cooperator will get

$$3 + 3\gamma + 3\gamma^2 + 3\gamma^3 + \dots = \frac{3}{1 - \gamma}$$

And the defector will get

$$5 + \gamma + \gamma^2 + \gamma^3 + \dots = 5 + \frac{\gamma}{1 - \gamma}$$

Axelrod, Evolution of Cooperation, 1984

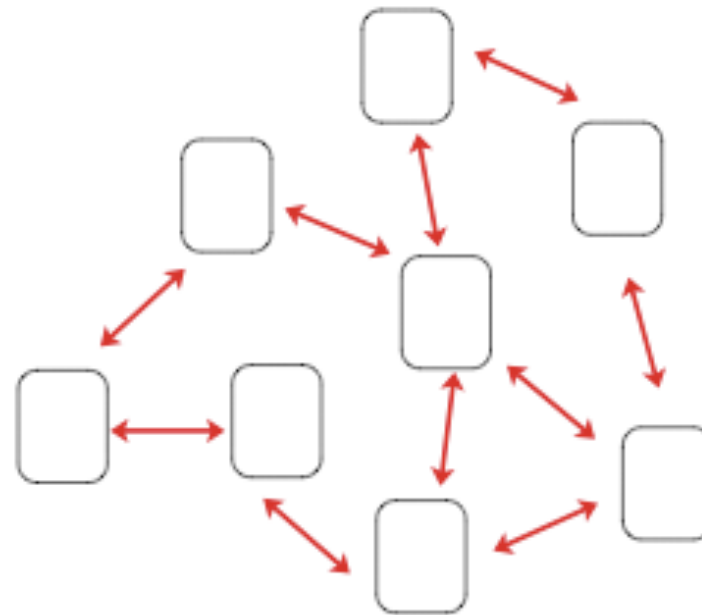
Groups play IPD

Winner's in human v human tournament used Tit-For-Tat strategies

- **Be nice:** cooperate, never be the first to defect.
- **Be provokable:** return defection for defection, cooperation for cooperation.
- **Don't be envious::** be fair with your *partner*.
- **Don't be too clever:** or, don't try to be tricky.

A genetic algorithm learns to beats the humans!

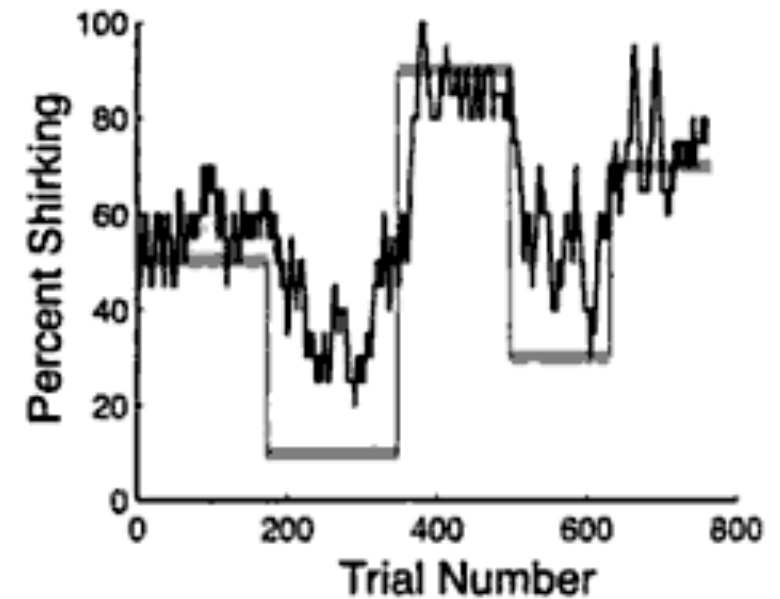
| | |
|----------|---|
| CC CC CC | D |
| CC CC CD | D |
| CC CC DC | C |
| ⋮ | |
| CD DC CC | D |
| ⋮ | |



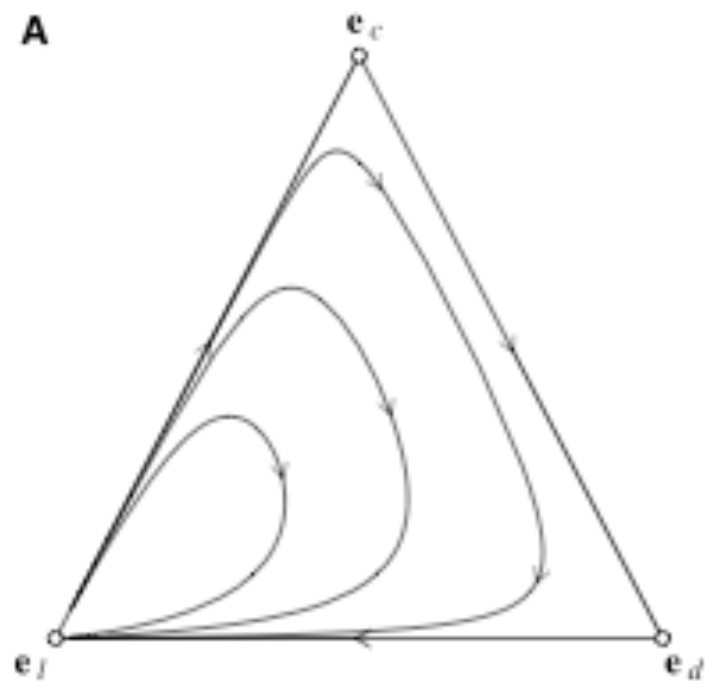
... because it punishes weak players

Probabilistic strategies e.g. 'Work or Shirk'

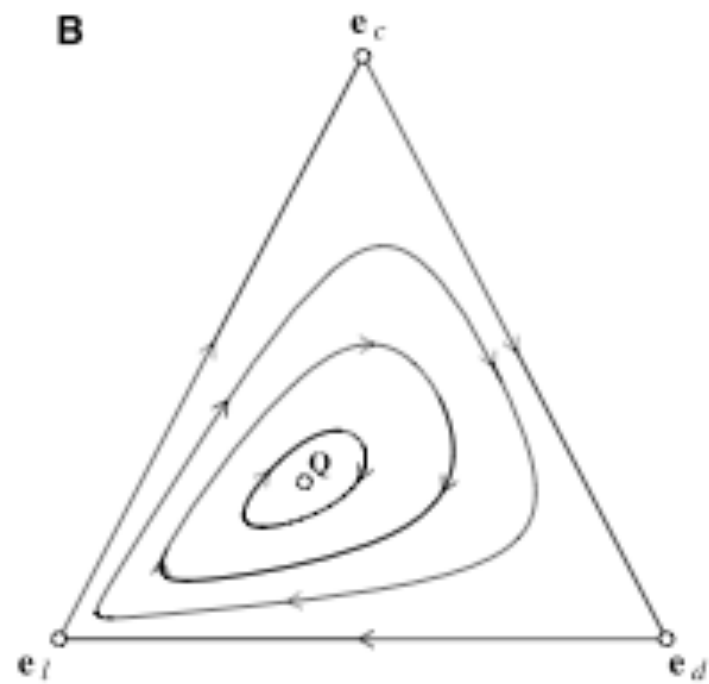
| | | Alice | |
|-----|-------|------------------|----------------|
| | | Insp. | ~Insp. |
| Bob | Shirk | 0 $-h$ | w $-w$ |
| | Work | $w-g$ $v-w-h$ | $w-g$ $v-w$ |



Monkeys can play work or shirk



$$r < 2$$



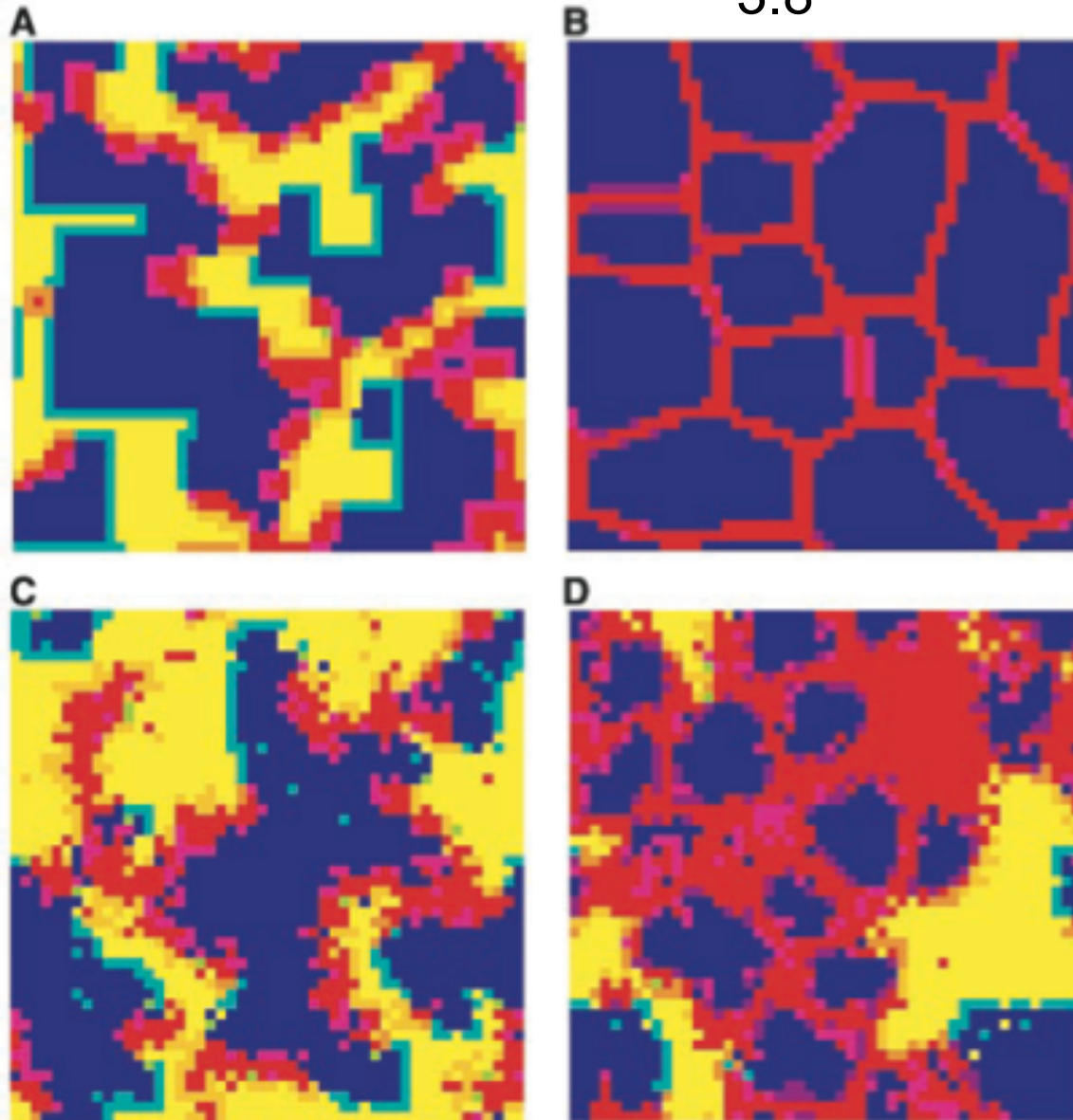
$$r > 2$$

Adopt the strategy of the best neighbor in 3x3

$r=2.2$

3.8

Sites adopt the strategy of a neighbor



80% of sites adopt the strategy of a neighbor w prob. \sim payoff diff.

Blue = cooperate; red = defect; yellow = sit out

1. Let α and δ be learning rates. Initialize,

$$Q(s, a) \leftarrow 0, \quad \pi(s, a) \leftarrow \frac{1}{|\mathcal{A}_i|}.$$

2. Repeat,

(a) From state s select action a with probability $\pi(s, a)$ with some exploration.

(b) Observing reward r and next state s' ,

$$Q(s, a) \leftarrow (1 - \alpha)Q(s, a) + \alpha \left(r + \gamma \max_{a'} Q(s', a') \right).$$

(c) Update $\pi(s, a)$ and constrain it to a legal probability distribution,

$$\pi(s, a) \leftarrow \pi(s, a) + \begin{cases} \delta & \text{if } a = \operatorname{argmax}_{a'} Q(s, a') \\ \frac{-\delta}{|\mathcal{A}_i| - 1} & \text{otherwise} \end{cases}.$$

$$R = \begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix} \quad C = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}$$

$$\begin{aligned}
V_r(\alpha, \beta) &= \alpha\beta r_{11} + \alpha(1 - \beta)r_{12} + \\
&\quad (1 - \alpha)\beta r_{21} + (1 - \alpha)(1 - \beta)r_{22} \\
&= u\alpha\beta + \alpha(r_{12} - r_{22}) + \\
&\quad \beta(r_{21} - r_{22}) + r_{22}
\end{aligned} \tag{1}$$

$$\begin{aligned}
V_c(\alpha, \beta) &= \alpha\beta c_{11} + \alpha(1 - \beta)c_{12} + \\
&\quad (1 - \alpha)\beta c_{21} + (1 - \alpha)(1 - \beta)c_{22} \\
&= u'\alpha\beta + \alpha(c_{12} - c_{22}) + \\
&\quad \beta(c_{21} - c_{22}) + c_{22}
\end{aligned} \tag{2}$$

where,

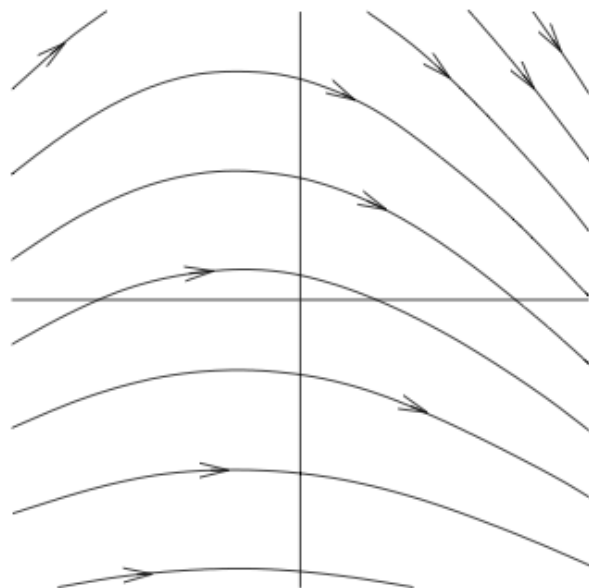
$$\begin{aligned}
u &= r_{11} - r_{12} - r_{21} + r_{22} \\
u' &= c_{11} - c_{12} - c_{21} + c_{22}.
\end{aligned}$$

$$\alpha_{k+1} = \alpha_k + \eta \frac{\partial V_r(\alpha_k, \beta_k)}{\partial \alpha_k}$$

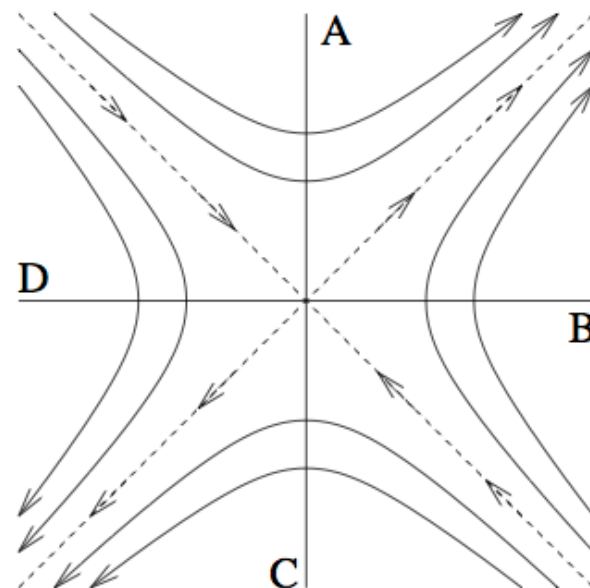
$$\beta_{k+1} = \beta_k + \eta \frac{\partial V_r(\alpha_k, \beta_k)}{\partial \beta_k}.$$

$$\begin{bmatrix} \frac{\partial \alpha}{\partial t} \\ \frac{\partial \beta}{\partial t} \end{bmatrix} = \begin{bmatrix} 0 & u \\ u' & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \begin{bmatrix} (r_{12} - r_{22}) \\ (c_{21} - c_{22}) \end{bmatrix}$$

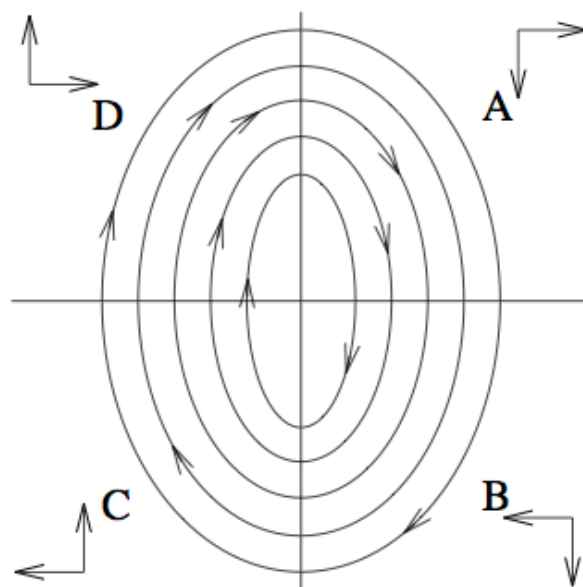
$$(\alpha^*, \beta^*) = \left(\frac{(c_{22} - c_{21})}{u'}, \frac{(r_{22} - r_{12})}{u} \right)$$



(a) U is not invertible

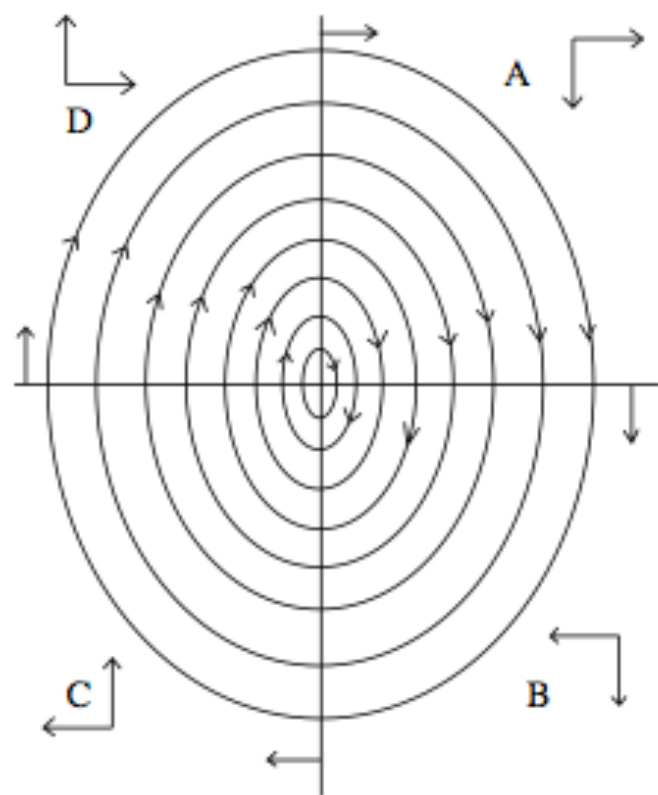


(b) U has real eigenvalues

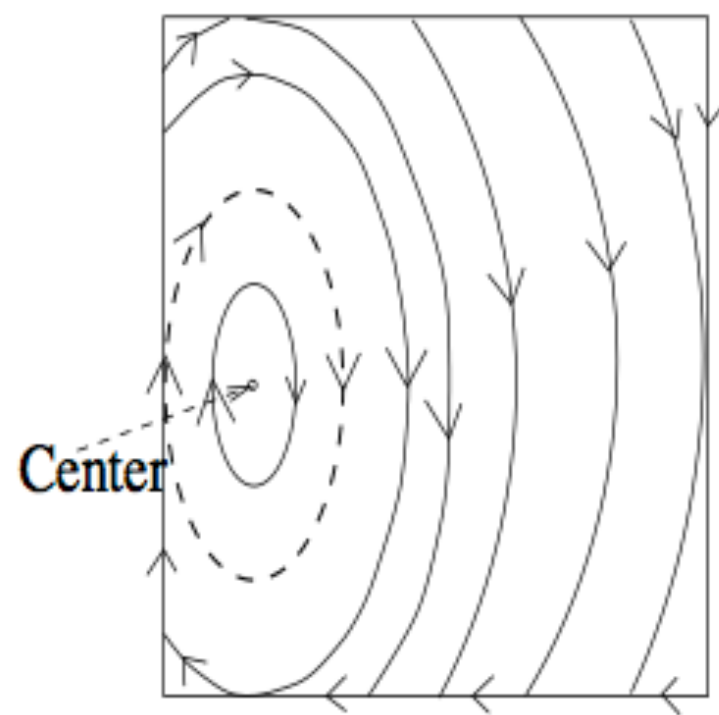


(c) U has imaginary eigenvalues

a)



b)



$$\ell_k^r = \begin{cases} \ell_{\min} & \text{if } V_r(\alpha_k, \beta_k) > V_r(\alpha^e, \beta_k) \\ \ell_{\max} & \text{otherwise} \end{cases} \quad \begin{array}{l} \text{WINNING} \\ \text{LOSING} \end{array}$$

$$\ell_k^c = \begin{cases} \ell_{\min} & \text{if } V_c(\alpha_k, \beta_k) > V_c(\alpha_k, \beta^e) \\ \ell_{\max} & \text{otherwise} \end{cases} \quad \begin{array}{l} \text{WINNING} \\ \text{LOSING} \end{array}$$

1. Let $\alpha, \delta_l > \delta_w$ be learning rates. Initialize,

$$Q(s, a) \leftarrow 0, \quad \pi(s, a) \leftarrow \frac{1}{|\mathcal{A}_i|}, \quad C(s) \leftarrow 0.$$

2. Repeat,

(a,b) Same as PHC in Table 1

(c) Update estimate of average policy, $\bar{\pi}$,

$$\begin{aligned} C(s) &\leftarrow C(s) + 1 \\ \forall a' \in \mathcal{A}_i \quad \bar{\pi}(s, a') &\leftarrow \bar{\pi}(s, a') + \frac{1}{C(s)} (\pi(s, a') - \bar{\pi}(s, a')). \end{aligned}$$

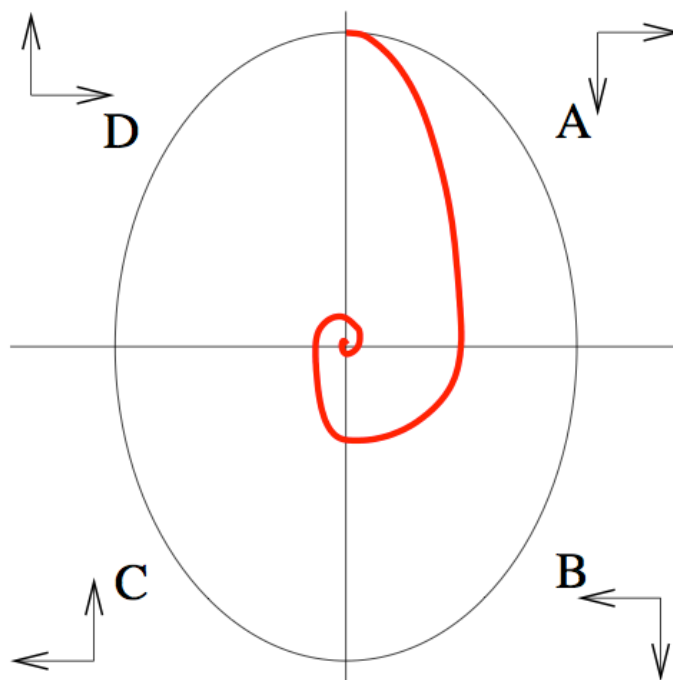
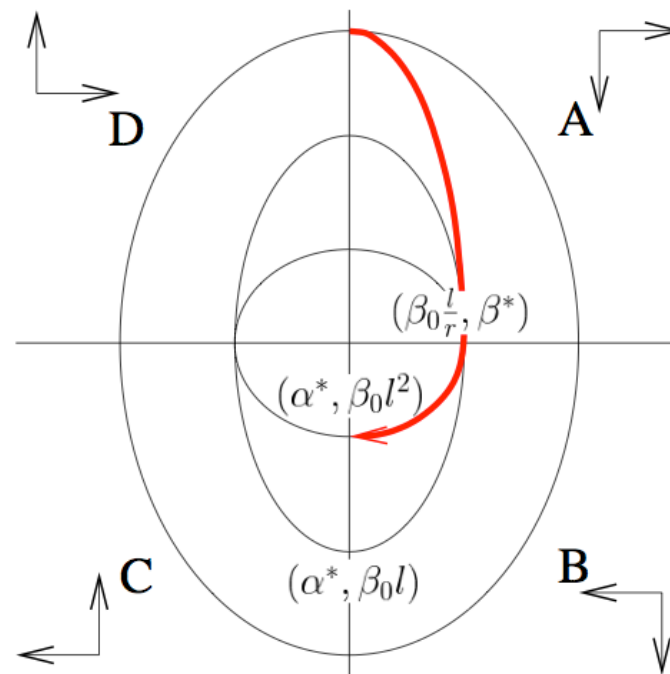
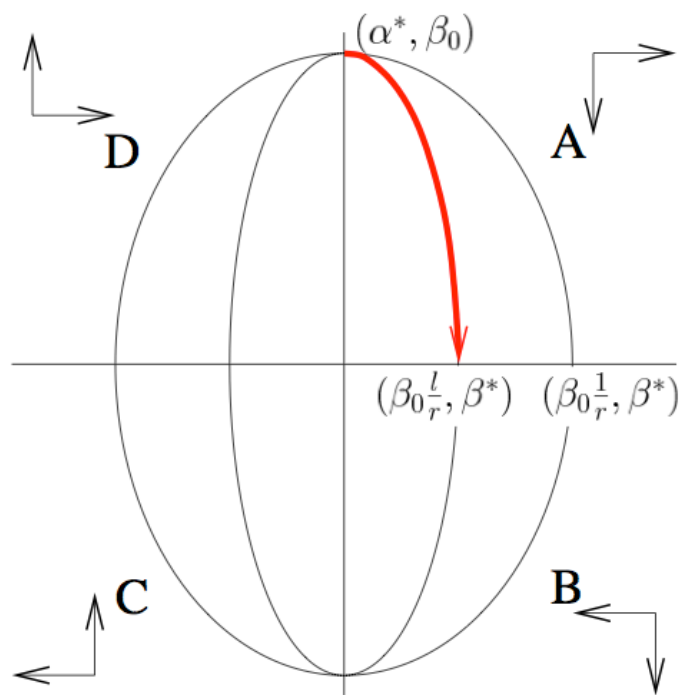
(d) Update $\pi(s, a)$ and constrain it to a legal probability distribution,

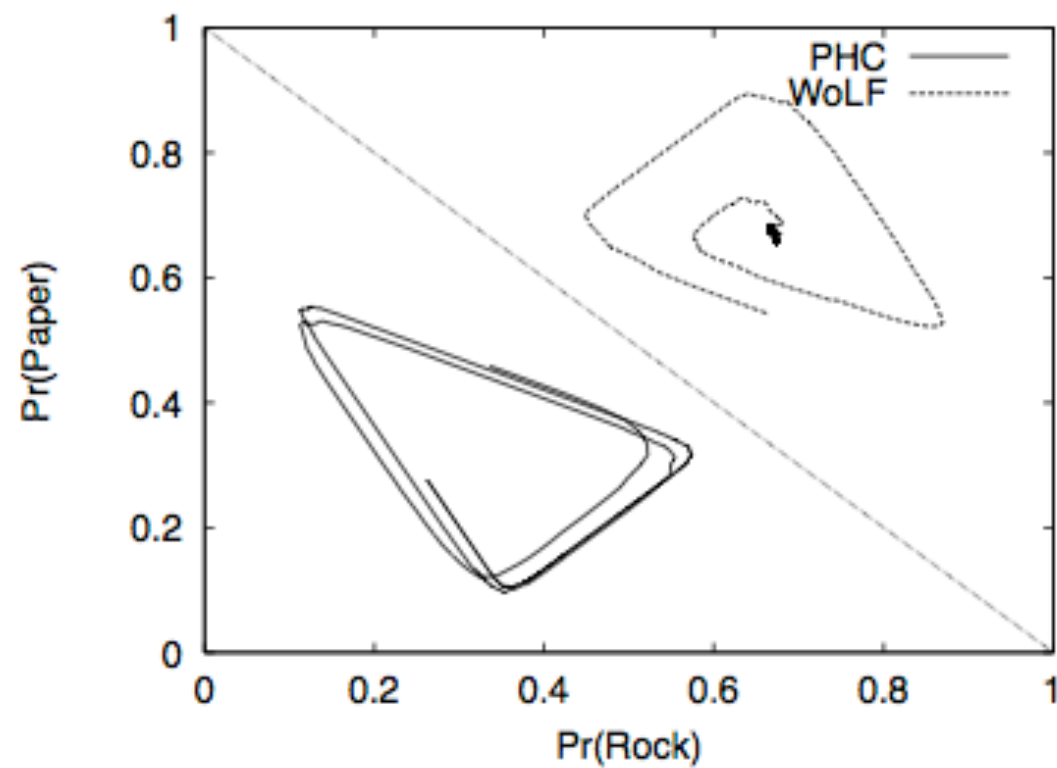
$$\pi(s, a) \leftarrow \pi(s, a) + \begin{cases} \delta & \text{if } a = \operatorname{argmax}_{a'} Q(s, a') \\ \frac{-\delta}{|\mathcal{A}_i| - 1} & \text{otherwise} \end{cases},$$

where,

$$\delta = \begin{cases} \delta_w & \text{if } \sum_a \pi(s, a) Q(s, a) > \sum_a \bar{\pi}(s, a) Q(s, a) \\ \delta_l & \text{otherwise} \end{cases}.$$

$$\begin{bmatrix} \frac{\partial \alpha}{\partial t} \\ \frac{\partial \beta}{\partial t} \end{bmatrix} = \begin{bmatrix} 0 & \ell^r(t)u \\ \ell^c(t)u' & 0 \end{bmatrix} \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \begin{bmatrix} \ell^r(t)(r_{12} - r_{22}) \\ \ell^c(t)(c_{21} - c_{22}) \end{bmatrix}$$





(b) Rock-Paper-Scissors Game

| \backslash to play | C | D |
|----------------------|---------------------|-----------------|
| opponent played C | $1 - \lambda\delta$ | $\lambda\delta$ |
| opponent played D | δ | $1 - \delta$ |

$$\delta S + (1 - \delta)P = P - \delta(P - S).$$

$$\delta < \frac{\epsilon}{P - S}.$$

| current \ next | CC | CD | DC | DD |
|----------------|-----------------------------|------------------------------------|------------------------------------|-----------------------------|
| CC | $(1 - \lambda\delta)^2$ | $\lambda\delta(1 - \lambda\delta)$ | $\lambda\delta(1 - \lambda\delta)$ | $(\lambda\delta)^2$ |
| CD | $\delta(1 - \lambda\delta)$ | $\lambda\delta^2$ | $(1 - \lambda\delta)(1 - \delta)$ | $\lambda\delta(1 - \delta)$ |
| DC | $\delta(1 - \lambda\delta)$ | $(1 - \lambda\delta)(1 - \delta)$ | $\lambda\delta^2$ | $\lambda\delta(1 - \delta)$ |
| DD | δ^2 | $\delta(1 - \delta)$ | $\delta(1 - \delta)$ | $(1 - \delta)^2$ |

$$\pi = \pi T$$

$$\pi = \left[\frac{1}{(1 + \lambda)^2}, \frac{\lambda}{(1 + \lambda)^2}, \frac{\lambda}{(1 + \lambda)^2}, \frac{\lambda^2}{(1 + \lambda)^2} \right]$$

