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Consistency of Vanishingly Smooth Fictitious play (In collaboration with Michel Benaïm, UNINE)

Mathieu Faure

Journées MAS, Toulouse, 2014.

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Settings		

- Player 1 (Decision Maker), Player 2 (Nature, environment),
- finite sets of actions I and L; sets of mixed actions : $X=\Delta(I),$ $Y=\Delta(L),$

$$X := \{ (x_i)_{i \in I}, \ x_i \ge 0, \ \sum_i x_i = 1 \}.$$

• payoff function of DM : π (I imes L matrix)

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- payoff function of DM : π ($I \times L$ matrix)
- we assume that agents play **repeatedly**. Let $h_n = (i_1, l_1, ..., i_n, l_n)$ history at time n.
- a strategy for DM is a map σ :

$$\cup_n \mathcal{H}_n \to \Delta(I), \ h_n \mapsto \sigma(h_n) \in \Delta(I).$$

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- a strategy for DM is a map σ :

$$\cup_n \mathcal{H}_n \to \Delta(I), \ h_n \mapsto \sigma(h_n) \in \Delta(I).$$

• A pair of strategies (σ, τ) induces a probability measure \mathbb{P} on $(I \times L)^{\mathbb{N}}$; we assume that agents play independently :

$$\mathbb{P}\left(i_{n+1}=i, l_{n+1}=l \mid \mathcal{H}_n\right) = \mathbb{P}\left(i_{n+1}=i \mid \mathcal{H}_n\right) \mathbb{P}\left(l_{n+1}=l \mid \mathcal{H}_n\right).$$

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Regret		

$$x_n := \frac{1}{n} \sum_{k=1}^n \delta_{i_k} \in X, \ y_n = \frac{1}{n} \sum_{k=1}^n \delta_{l_k} \in Y, \ \pi_n := \frac{1}{n} \sum_{k=1}^n \pi(i_k, l_k).$$

Define

$$\Pi: Y \to \mathbb{R}: \ y \mapsto \max_i \pi(i, y).$$

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Definition (regret at stage n)

 $e_n =$

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$$e_n = \underbrace{\max_{i \in I} \pi(i, y_n)}_{\Pi(y_n)} - \underbrace{\frac{1}{n} \sum_{k=1}^n \pi(i_k, l_k)}_{\pi_n}.$$

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Consistency		

Definition

Player 1's strategy is *consistent* if, regardless of the strategy au of nature,

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\limsup_{n \to +\infty} e_n \le 0, \text{ almost surely.}
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It is η -consistent provided

 $\limsup_{n \to +\infty} e_n \leq \eta, \text{ almost surely.}$

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Fictitious play		

Let **br** be the *best response map* :

```
\mathbf{br}: Y \rightrightarrows X, \ y \mapsto Argmax_{x \in X} \pi(x, y)
```

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Definition

The strategy σ of DM is a *fictitious play* strategy if, $\forall n \in \mathbb{N}$,

 $\sigma(h_n) \in \mathbf{br}(\tilde{y}_n),$

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with
$$\tilde{y}_n = \frac{1}{n+1} \underbrace{y_0}_{\text{prior}} + \frac{n}{n+1} y_n$$
.

Remark

FP is not consistent

Mathieu Faure

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Perturbed payoff function and Smooth best response

Let ε be a small positive parameter

Definition (Perturbed payoff)

The (ρ, ε) -perturbed payoff relative to the original payoff function π is defined by

 $\pi^{\varepsilon}(x,y) = \pi(x,y) + \varepsilon \rho(x),$

where ρ is **concave** and its gradient explodes at the boundary.

We have :

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We have :

- hence for all $y \in Y$, $Argmax_{x \in X} \pi^{\varepsilon}(\cdot, y)$ reduces to one point,
- Thus we can define the smooth best response map
 br^ε : Y → Int(X) :

$$\mathbf{br}^{\varepsilon}(y) := Argmax_{x \in X} \pi^{\varepsilon}(x, y).$$

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Particular case		

$$\rho(x) = -\sum_{i} x_i \log x_i.$$

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Particular case		

$$\rho(x) = -\sum_{i} x_i \log x_i.$$

In that case, we can give an explicit formula for the perturbed best response map :

$$\left(\mathbf{br}^{\varepsilon}(y)\right)_{i} = \frac{\exp\left(\frac{1}{\varepsilon}\pi(i,y)\right)}{\sum_{k}\exp\left(\frac{1}{\varepsilon}\pi(k,y)\right)}$$

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Definition (Smooth fictitious play)

 σ is a smooth fictitious play (SFP(arepsilon)) strategy for player 1 if, for all $n\in\mathbb{N}$

$$\sigma(h_n) = \mathbf{br}^{\varepsilon}(y_n),$$

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Interpretations		

- One way to interpret SFP((ε)) strategies is that the agent chooses to randomize his moves, playing the best response to the average moves of the opponent, with respect to a slightly perturbed version of his payoff function;
- Another possible interpretation of SFP(ε) strategies is that his payoffs are actually perturbed by i.i.d. random shocks (usually called stochastic fictitious play).

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Smooth fictitious	play	

Theorem (Fudenberg-Levine)

Given $\eta > 0$, $SFP(\varepsilon)$ is η -consistent, provided ε is small enough.

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Smooth fictitious	play	

Theorem (Fudenberg-Levine)

Given $\eta > 0$, $SFP(\varepsilon)$ is η -consistent, provided ε is small enough.

Benaïm-Hofbauer-Sorin (2006) gave an alternative proof using stochastic approximations technics : we have $x_{n+1} - x_n = \frac{1}{n+1} \left(\delta_{i_{n+1}} - x_n \right)$. Hence

$$\begin{aligned} x_{n+1} - x_n &= \frac{1}{n+1} \left(\underbrace{\mathbb{E}\left(\delta_{i_{n+1}} \mid \mathcal{H}_n\right)}_{\mathbf{br}^{\epsilon}(y_n)} - x_n + \underbrace{\left(\delta_{i_{n+1}} - \mathbb{E}\left(\delta_{i_{n+1}} \mid \mathcal{H}_n\right)\right)}_{\mathsf{martingale difference}} \right) \\ y_{n+1} - y_n &= \frac{1}{n+1} \left(\underbrace{\mathbb{E}\left(\delta_{l_{n+1}} \mid \mathcal{H}_n\right)}_{\tau(h_n)} - y_n + \underbrace{\left(\delta_{l_{n+1}} - \mathbb{E}\left(\delta_{l_{n+1}} \mid \mathcal{H}_n\right)\right)}_{\mathsf{martingale difference}} \right) \end{aligned}$$

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Stochastic Approximation Algorithms, the ODE method

M compact subset of \mathbb{R}^d . Let $(v_n)_n$ be a M-valued stochastic process governed by the recursive formula

$$v_{n+1} - v_n = \frac{1}{n+1}(f(v_n) + U_{n+1}),$$

where

Stochastic Approximation Algorithms, the ODE method

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where

- f is a *Lipschitz* vector field, inducing a flow Φ on M,
- $(U_n)_n$ is a bounded sequence of random variables.

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- f is a *Lipschitz* vector field, inducing a flow Φ on M,
- $(U_n)_n$ is a *bounded* sequence of random variables.

Question : can we say anything about the *qualitative* asymptotic behavior of $(v_n)_n$?

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Mean ODE		

$$v_{n+1} = v_n + \frac{1}{n+1}(f(v_n) + U_{n+1}), \tag{1}$$

Consider the mean ODE :

$$\dot{v} = f(v). \tag{2}$$

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Moon ODE		

$$v_{n+1} = v_n + \frac{1}{n+1}(f(v_n) + U_{n+1}), \tag{1}$$

Consider the mean ODE :

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$$\dot{v} = f(v). \tag{2}$$

Link between (1) and (2) : if $(U_n)_n$ is a martingale difference : $\mathbb{E}(U_{n+1} | \mathcal{F}_n) = 0$, the asymptotic behavior of the paths $(v_n(\omega))_n$ should be related to the solution curves of (2) (*ODE method*) Backgrounds and settings 00000000

Convergence of Stochastic Approximation Algorithms

Theorem (Limit set theorem, Benaïm, 1996)

- a) The limit set of $(v_n)_n$ is almost surely compact convex, invariant and attractor-free,
- b) if A is a global attractor, $\mathcal{L}((v_n)_n) \subset A$ almost surely.

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Theorem (Benaïm, Hofbauer and Sorin, 2005)

It also holds when f is a (reasonably regular) set-valued map.

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Back to $SFP(\varepsilon)$		

State variable : $v_n = (x_n, y_n, \pi_n)$. We have

$$v_{n+1} - v_n \in \frac{1}{n+1}(F^{\varepsilon}(v_n) + U_{n+1}),$$

where

$$F^{\varepsilon}(x, y, \pi) = \{ (\mathbf{br}^{\varepsilon}(y_n), \tau, \pi(\mathbf{br}^{\varepsilon}(y_n), \tau), \ \tau \in Y \} - (x, y, \pi) \}$$

- The set-valued map $F^{arepsilon}$ is very regular,
- As a consequence, BHS results apply and, if the differential inclusion $\dot{v}(t) \in F^{\varepsilon}(v(t))$ admits a global attractor A then $\mathcal{L}((v_n)_n) \subset A$.

Proof of η -consistency via stochastic approximations

Theorem (Benaïm-Hofbauer-Sorin, 2006)

Given $\eta > 0$, for ε small enough we have

- the set $A := \{v = (x, y, \pi) : \Pi(y) \pi \le \eta\}$ contains a global attractor for the differential inclusion $\dot{v}(t) \in F^{\varepsilon}(v(t))$,
- consequently

$$\limsup_{n} \Pi(y_n) - \pi_n \le \eta \text{ almost surely.}$$

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A natural questio	n	

What happens when the parameter ε is replaced by a vanishing sequence $\varepsilon_n \downarrow 0$?

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A natural question		

What happens when the parameter ε is replaced by a vanishing sequence $\varepsilon_n \downarrow 0\,?$

Definition (Vanishingly Smooth fictitious play)

Given a sequence $\varepsilon_n \downarrow 0$, we say that DM plays accordingly to a vanishingly smooth fictitious play strategy (VSFP(ε_n)) if, for all $n \in \mathbb{N}$,

 $\sigma(h_n) = \mathbf{br}^{\varepsilon_{\mathbf{n}}}(y_n).$

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Remark

VSFP is not consistent, if
$$\varepsilon_n = \frac{1}{n}$$

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A counter-Example		

2-player matching pennies and that nature uses (l,r,l,r...). $\varepsilon_n = 1/n$, prior $y_0 = (1/3,2/3)$, then

$$\tilde{y}_{2n} = \frac{1}{2n+1}y_0 + \frac{n}{n+1}y_{2n} = \left(\frac{1}{2} - \frac{1}{6(2n+1)}, \frac{1}{2} + \frac{1}{6(2n+1)}\right).$$

After a few lines of calculus one gets :

$$\mathbf{br}^{\varepsilon_{\mathbf{n}}}(\tilde{y}_{2n}) \longrightarrow_{n \to +\infty} \left(\frac{1}{2} - c, \frac{1}{2} + c\right).$$

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Vanishingly Smooth Fictitious play ○○●

Statement of the main result

Theorem (Benaïm, F.)

If, for some $\alpha < 1$, $\varepsilon_n \geq \frac{1}{n^{\alpha}}$ then $VSFP(\varepsilon_n)$ is consistent.

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Statement of the main result

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If, for some $\alpha < 1$, $\varepsilon_n \geq \frac{1}{n^{\alpha}}$ then $VSFP(\varepsilon_n)$ is consistent.

• The proof relies on set-valued dynamical systems approach, similarily to BHS,

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Statement of the main result

Theorem (Benaïm, F.)

If, for some $\alpha < 1$, $\varepsilon_n \geq \frac{1}{n^{\alpha}}$ then $VSFP(\varepsilon_n)$ is consistent.

- The proof relies on set-valued dynamical systems approach, similarily to BHS,
- unfortunately, we now need to deal with *nonautonomous* differential inclusions,