

# **Calibrated Learning and Global Convergence**

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## *Global Convergence?*

- “grail” of learning research: global convergence theorem for convincing learning processes
- easy to construct examples of learning processes that don’t converge
- non-convergence looks like cob-web; people repeat the same mistakes over and over; not terrifically plausible
- we seem to see much “equilibriumness” around us (traffic example)
- “full Bayes learning” (Kalai-Lehrer) results in convergence to Nash equilibrium
- Peyton just argued that such learning isn’t really possible
- I’ll try to convince you that “all sensible” learning procedures lead in the long-run to correlated equilibrium

- I'll start by motivating learning processes from an individual perspective (i.e. processes that “work”)
- I'm only going to talk about pure forecasting (no causality)

### ***“Classical” Case of Fictitious Play***

- keep track of frequencies of opponents' play
- begin with an initial or prior sample
- play a best-response to historical frequencies
- not well defined if there are ties, but for generic payoff/prior there will be no ties
- optimal procedure against i.i.d. opponents

- how well does fictitious play do if the i.i.d. assumption is wrong?

## How well can fictitious play do in the long-run?

- notice that fictitious play only keeps track of frequencies: can fictitious play do as well in the long-run as if those frequencies (but not the order of the sample) was known in advance? Notice the weakening of the criterion
- Universal Consistency

let  $u_t^i$  be actual utility at time  $t$ , let  $\phi_t^{-i}$  be frequency of opponents' play (joint distribution over  $S^{-i}$ )

suppose that for *all* (note that this does not say “for almost all”) sequences of opponent play

$$\liminf_{T \rightarrow \infty} (1/T) \sum_{t=1}^T u_t^i - \max_{s^i} u^i(s^i, \phi_T^{-i}) \geq 0$$

then the learning procedure is *universally consistent*

*Is fictitious play universally consistent? Fudenberg and Kreps example*

0,0	1,1
1,1	0,0

this coordination game is played by two identical players

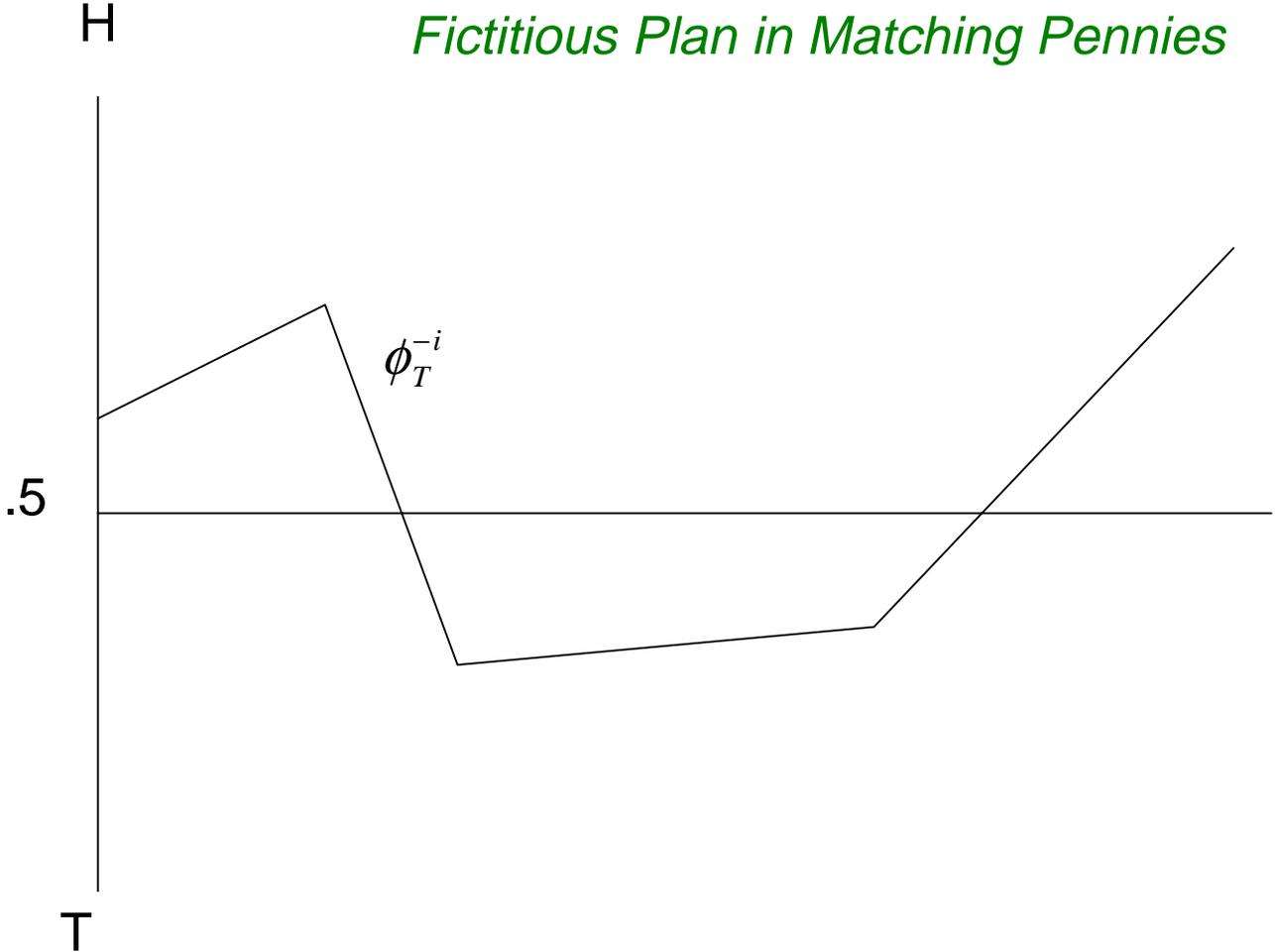
suppose they use *identical deterministic* learning procedures

then they play UL or DR and get 0 in every period

this is not individually rational, let alone universally consistent

*Theorem [Monderer, Samet, Sela; Fudenberg, Levine]:* fictitious play is consistent provided the frequency with which the player switches strategies goes to zero

*Fictitious Plan in Matching Pennies*



## Smooth Fictitious Play

instead of maximizing  $u^i(s^i, \phi_{t-1}^i)$  maximize  $u^i(\sigma^i, \phi_{t-1}^i) + \lambda v^i(\sigma^i)$

where  $v^i$  is smooth, concave and has derivatives that are unbounded at the boundary of the unit simplex

example: the *entropy*  $v^i(\sigma^i) = -\sum_{s^i} \sigma^i(s^i) \log \sigma^i(s^i)$

as  $\lambda \rightarrow 0$  this results in an approximate optimum to the original problem

however the solution to  $u^i(\sigma^i, \phi_{t-1}^i) + \lambda v^i(\sigma^i)$  is smooth and interior (always puts positive weight on all pure strategies)

*Theorem [Blackwell, Hannan, Fudenberg and Levine and others]:*  
smooth fictitious play is  $\varepsilon$  universally consistent with  $\varepsilon \rightarrow 0$  as  $\lambda \rightarrow 0$

## Calibration

Notice that pattern recognition is ruled out

Instead, use conditional probabilities; specifically

$$\phi_T^{-i}(\tilde{s}^i)$$

$$\liminf_{T \rightarrow \infty} (1/T) \sum_{t=1}^T u_t^i - \sum_{\tilde{s}^i} \max_{s^i} u^i(s^i, \phi_T^{-i}(\tilde{s}^i)) \geq 0$$

## *Interpretation of Calibration*

weather forecasting example: calibrated beliefs, versus calibrated actions

**consequence of universal calibration: global convergence to the set of correlated equilibria**

**Foster and Vohra: there are universally calibrated algorithms**

*How to do it?*

$\hat{\sigma}^i(\phi)$  smooth fictitious play

suppose you play  $\tilde{\sigma}^i$

with probability  $\tilde{\sigma}^i(s^i)$  you play  $s^i$

if you choose  $s^i$  then you “should” play  $\hat{\sigma}^i(\phi_{t-1}^{-i}(s^i))$

so overall, you “should” play  $\sum_{s^i} \tilde{\sigma}^i(s^i) \hat{\sigma}^i(\phi_{t-1}^{-i}(s^i))$

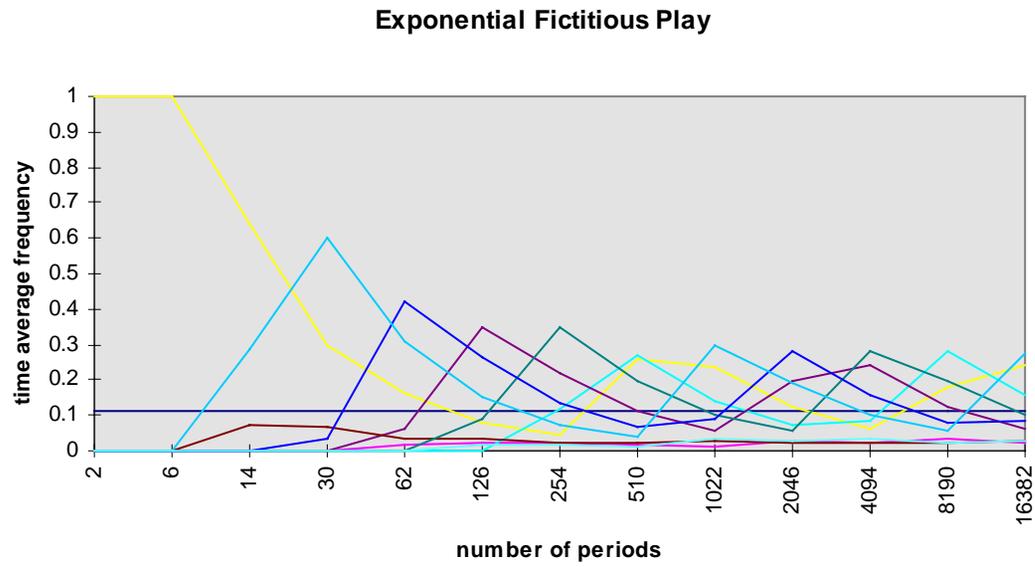
a fixed point problem then:  $\tilde{\sigma}^i(s^i) = \sum_{s^i} \tilde{\sigma}^i(s^i) \hat{\sigma}^i(\phi_{t-1}^{-i}(s^i))$

easy to solve, and indeed the solution is calibrated

## *Shapley Example*

	A	M	B
A	0,0	0,1	1,0
M	1,0	0,0	0,1
B	0,1	1,0	0,0

smooth fictitious play (time in logs)



condition on opponents last period play (time in logs)

### Learning Conditional on Opponent's Play

