

A Proofs

Lemma 6. Let π and β be two behavioural strategies, Π and B two mixed strategies that are realization equivalent to π and β , and $\lambda_1, \lambda_2 \in \mathbb{R}_{\geq 0}$ with $\lambda_1 + \lambda_2 = 1$. Then for each information state $u \in \mathcal{U}$,

$$\mu(u) = \pi(u) + \frac{\lambda_2 x_\beta(\sigma_u)}{\lambda_1 x_\pi(\sigma_u) + \lambda_2 x_\beta(\sigma_u)} (\beta(u) - \pi(u))$$

defines a behavioural strategy μ at u and μ is realization equivalent to the mixed strategy $M = \lambda_1 \Pi + \lambda_2 B$.

Proof. The realization plan of $M = \lambda_1 \Pi + \lambda_2 B$ is

$$x_M(\sigma_u) = \lambda_1 x_\Pi(\sigma_u) + \lambda_2 x_B(\sigma_u), \quad \forall u \in \mathcal{U}.$$

and due to realization-equivalence, $x_\Pi(\sigma_u) = x_\pi(\sigma_u)$ and $x_B(\sigma_u) = x_\beta(\sigma_u) \forall u \in \mathcal{U}$. This realization plan induces a realization equivalent behavioural strategy

$$\begin{aligned} \mu(u, a) &= \frac{x_M(\sigma_u a)}{x_M(\sigma_u)} \\ &= \frac{\lambda_1 x_\pi(\sigma_u a) + \lambda_2 x_\beta(\sigma_u a)}{\lambda_1 x_\pi(\sigma_u) + \lambda_2 x_\beta(\sigma_u)} \\ &= \frac{\lambda_1 x_\pi(\sigma_u) \pi(u, a) + \lambda_2 x_\beta(\sigma_u) \beta(u, a)}{\lambda_1 x_\pi(\sigma_u) + \lambda_2 x_\beta(\sigma_u)} \\ &= \pi(u, a) + \frac{\lambda_2 x_\beta(\sigma_u) (\beta(u, a) - \pi(u, a))}{\lambda_1 x_\pi(\sigma_u) + \lambda_2 x_\beta(\sigma_u)}. \end{aligned}$$

□

Theorem 7. Let π_1 be an initial behavioural strategy profile. The extensive-form process

$$\begin{aligned} \beta_{t+1}^i &\in b_{\epsilon_{t+1}}^i(\pi_t^{-i}), \\ \pi_{t+1}^i(u) &= \pi_t^i(u) + \frac{\alpha_{t+1} x_{\beta_{t+1}^i}(\sigma_u) (\beta_{t+1}^i(u) - \pi_t^i(u))}{(1 - \alpha_{t+1}) x_{\pi_t^i}(\sigma_u) + \alpha_{t+1} x_{\beta_{t+1}^i}(\sigma_u)} \end{aligned}$$

for all players $i \in \mathcal{N}$ and all their information states $u \in \mathcal{U}^i$, with $\alpha_t \rightarrow 0$ and $\epsilon_t \rightarrow 0$ as $t \rightarrow \infty$, and $\sum_{t=1}^{\infty} \alpha_t = \infty$, is realization-equivalent to a generalised weakened fictitious play in the normal-form and therefore the average strategy profile converges to a Nash equilibrium in all games with the fictitious play property.

Proof. By induction. Assume π_t and Π_t are realization equivalent and $\beta_{t+1} \in b_{\epsilon_{t+1}}(\pi_t)$ is an ϵ_{t+1} -best response to π_t . By Kuhn's Theorem, let B_{t+1} be any mixed strategy that is realization equivalent to β_{t+1} . Then B_{t+1} is an ϵ_{t+1} -best response to Π_t in the normal-form. By Lemma 6, the update in behavioural policies, π_{t+1} , is realization equivalent to the following update in mixed strategies

$$\Pi_{t+1} = (1 - \alpha_{t+1}) \Pi_t + \alpha_{t+1} B_{t+1}$$

and thus follows a generalised weakened fictitious play. □

B Algorithms

Algorithm 3 FSP with FQI and simple counting model

Instantiate functions FICTITIOUSSELFPLAY and GENERATEDATA as in algorithm 2

function UPDATERLMEMORY($\mathcal{M}_{RL}^i, \mathcal{D}^i$)

$\mathcal{T} \leftarrow$ Extract from \mathcal{D}^i episodes that consist of transitions $(u_t, a_t, r_{t+1}, u_{t+1})$ from player i 's point of view. Add \mathcal{T} to \mathcal{M}_{RL}^i , replacing oldest data if the memory is full.

return \mathcal{M}_{RL}^i

end function

function UPDATESLMEMORY($\mathcal{M}_{SL}^i, \mathcal{D}^i$)

$\mathcal{D}_\beta^i \leftarrow$ Extract all episodes from \mathcal{D}^i where player i chose their approximate best response strategy.

$\mathcal{B} \leftarrow$ Extract from \mathcal{D}_β^i data that consist of pairs (u_t, μ_t) , where μ_t is player i 's strategy at information state u_t at the time of sampling the respective episode.

return \mathcal{B}

end function

function REINFORCEMENTLEARNING(\mathcal{M}_{RL}^i)

Initialize FQI with previous iteration's Q -values.

$\beta \leftarrow$ FQI(\mathcal{M}_{RL}^i)

return β

end function

function SUPERVISEDLEARNING(\mathcal{M}_{SL}^i)

Initialize counting model from previous iteration.

for each (u_t, μ_t) in \mathcal{M}_{SL}^i **do**

$\forall a \in \mathcal{A}(u_t) : N(u_t, a) \leftarrow N(u_t, a) + \mu_t(a)$

$\forall a \in \mathcal{A}(u_t) : \pi(u_t, a) \leftarrow \frac{N(u_t, a)}{N(u_t)}$

end for

return π

end function

C River Poker

In our experiments, one instance of River poker implements a Texas Hold'em scenario, where the first player called a raise pre flop, check/raised on the flop and bet the turn. The community cards were set to KhTc7d5sJh. The players' distributions assume that player 1 likely holds one combination of "K4s-K2s, KTo-K3o, QTo-Q9o, J9o+, T9o, T7o, 98o, 96o" with probability 0.99 and a uniform random holding with probability 0.01. Similarly, player 2 is likely to hold one combination of "QQ-JJ, 99-88, 66, AQs-A5s, K6s, K4s-K2s, QTs, Q7s, JTs, J7s, T8s+, T6s-T2s, 97s, 87s, 72s+, AQo-A5o, K6o, K4o-K2o, QTo, Q7o, JTo, J7o, T8o+, T6o-T4o, 97o, 87o, 75o+".