

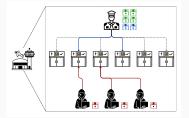
# Team-Fictitious Play for Reaching Team-Nash Equilibrium in Multi-team Games

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Two-team games are common in many scenarios.



**Figure 1:** Example two team game (**Airport Security**): Consider a security chief guarding the six gates of an airport against three different autonomous intruders.

#### **Key Question**

In such multi-team games, can agents within teams learn to coordinate and act according to the best team strategy without explicit communication?

- Common independent algorithms do not have any guarantees for joint team behavior.
- Prior works assume that agents can communicate beforehand and act as if they are a single agent during the game.

#### **Main Difficulty**

While a team tries to learn the best strategy, other teams will also learn and change strategies.

## Team (Potential) Games

- All players have aligning objectives
- There exist a common potential function φ, with the following property: If any player changes their action while the rest keep it the same, change in the payoff = change in the potential function.

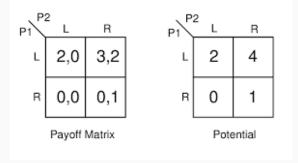


Figure 2: Example Potential Game



Figure 3: Multi-team Game

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We focus on competitive teams: Zero-sum Potential Team Games (ZSPTG)

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• Possibly a graph structure.

Two-team ZSPTG can be generalized to multi-team ZSPTG with adding the condition of separable potential functions.

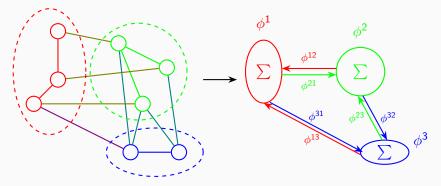


Figure 4: Example multi-team ZSPTG

### Team Nash Equilibrium

#### Definition

Given the strategy profile of teams  $\pi := \{\pi^m \in \Delta(\underline{A}^m)\}_{m \in \mathcal{T}}$ , we define the team-Nash gap for team m as  $\mathsf{TNG}(\pi) := \sum_{m \in \mathcal{T}} \mathsf{TNG}^m(\pi)$ , with  $\mathsf{TNG}(\pi)$  is defined as  $\mathsf{TNG}^{m}(\pi) := \max_{\tilde{\pi}^{m} \in \mathcal{A}(A^{m})} \left\{ \phi^{m}(\tilde{\pi}^{m}, \pi^{-m}) \right\} - \phi^{m}(\pi),$ where  $\pi^{-m} := \{\pi^{\ell}\}_{\ell \neq m}$ . Correspondingly, we say that the strategy profile of teams  $\pi$  is  $\epsilon$ -TNE if  $\mathsf{TNG}(\pi) \leq \epsilon.$ 

For two-teams, this is also known as team-maxmin equilibrium!

- Log-linear learning (Converges to near efficient equilibrium in potential games)
  - Only a single player can change action
  - Keep track of the last actions of others
  - Soft best response to the last actions of teammates
- (Smoothed) Fictitious Play (Converges to nash equilibrium in zero-sum polymatrix games)
  - Every player updates their action
  - Keep track of beliefs about every agent (average of actions they played)
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Let's combine these two algorithms!

- In each team, only a single player changes action (can be relaxed for independent case)
- Keep track of beliefs about joint actions of opponent teams and last actions of the teammates
- Soft best response to the beliefs and last actions

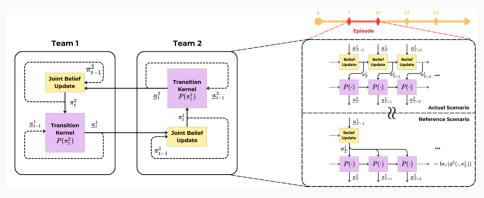
#### Theorem

Given a ZSPTG characterized by  $\langle \mathcal{T}, (A^i, u^i)_{i \in \mathcal{I}} \rangle$ , let every agent follow either Team-FP or Independent Team-FP Algorithm. If stepsize assumption holds, then the team-Nash gap for  $\pi_k := (\pi_k^m)_{m \in \mathcal{T}}$  satisfies

 $\limsup_{k \to \infty} \operatorname{TNG}(\pi_k) \leq \begin{cases} \tau \log |A| & \text{for Team-FP} \\ \tau \log |A| + |\mathcal{T}|^2 \overline{\phi} \cdot \Lambda(\delta, \epsilon) & \text{for Independent Team-FP} \end{cases}$ 

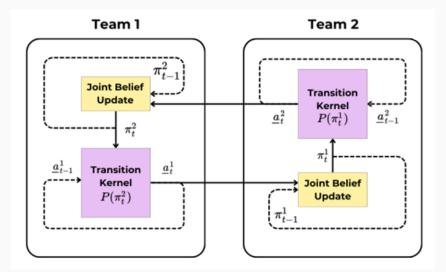
almost surely, where  $\overline{\phi} := \max_{(m,l,a)} |\phi^{ml}(a)|$ .

#### **Proof Sketch**

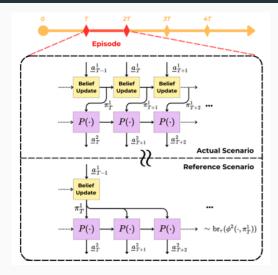


**Figure 5:** Team-FP Algorithm Dynamics for two teams (left), and the main proof idea (right). We show the Markov Chain of a reference scenario where beliefs  $\pi_t^1$  do not change, behaves similar to the actual scenario.

#### **Proof Sketch**



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Fictionally, we split the horizon into T-epoch lengths!

- The action profiles form a Markov chain within an epoch in the fictional scenario!
- The stationary distribution of the fictional scenario Markov chain:  $\mu^m_{(n)}(\underline{a}^m)$
- The action distribution of the actual scenario:  $\mu_{(n),k}^m := \mathrm{E}[\underline{a}_k^m \mid \mathcal{F}_{(n)}]$
- The difference  $\|\mu_{(n),k}^m \mu_{(n)}^m\|$  is bounded with arbitrarily small bounds.
- Using stochastic differential inclusion methods on the cumulative epoch update,

$$\pi_{(n+1)}^{m} = (1 - \beta_{(n)})\pi_{(n)}^{m} + \beta_{(n)} \left(\hat{\mu}_{(n),\star}^{m} + \omega_{(n+1)}^{m} + e_{(n)}^{m}\right),$$

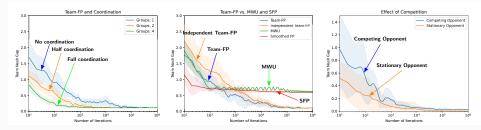
we obtain convergence.

We expect Team-FP to converge in other type of games where FP converges:

- Potential games
- 2xN games

We also provide a finite-horizon Markov Game generalization of Team-FP!

### Numerical Results

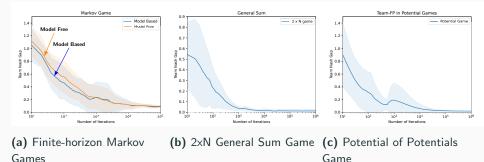


(a) Varying group sizes of 1, (b) Team-FP Algorithm 2. and 4.

(Independent) compared to Smoothed FP, and MWU

(c) Competitive vs Stationary Environment

Figure 6: All the above figures show the variation of TNG over time. (a) Comparison of different levels of explicit coordination for Team-FP: independent agents (group size 1), pairs of cooperating agents (group size 2), and fully coordinated teams (group size 4). (b) Performance of Team-FP and Independent Team-FP compared to Multiplicative Weights Update (MWU) and Smoothed FP (SFP) algorithms in a 2-team ZSPTG. (c) Convergence of Team-FP against stationary and competitive opponents in a 3-team ZSPTG.



**Figure 7:** All the above figures describes the variation of TNG over iterations for Algorithms that are related to but outside the scope of ZSPTG. (a) The model-free and model-based finite-horizon Markov games for extension Algorithms of Team-FP, for a game of 2-team each with 2 agents, with 2 states and 10 horizon length. (b) The behavior of Team-FP dynamics in a 2×N general sum game, where a team competes against a single agent with random rewards. (c) The behavior of Team-FP dynamics in a potential game over the underlying potential functions.

Yes! The initial example also show convergence of average joint actions of intruders to the Team Nash Equilibrium.

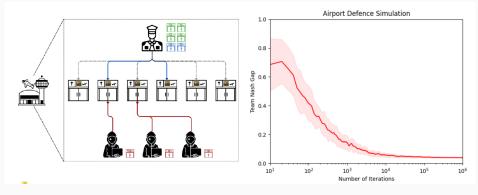


Figure 8: Airport Security Example