# Controlling Behavioral Diversity in Multi-Agent Reinforcement Learning


ICML International Conference On Machine Learning

UNIVERSITY OF CAMBRIDGE

Matteo Bettini, Ryan Kortvelesy, Amanda Prorok

Department of Computer Science and Technology, University of Cambridge

PROROKLAB


Website

## Why care?

### The role of diversity in collective intelligence

Multi-agent and multi-robot cooperative tasks often need or benefit from behavioral heterogeneity.

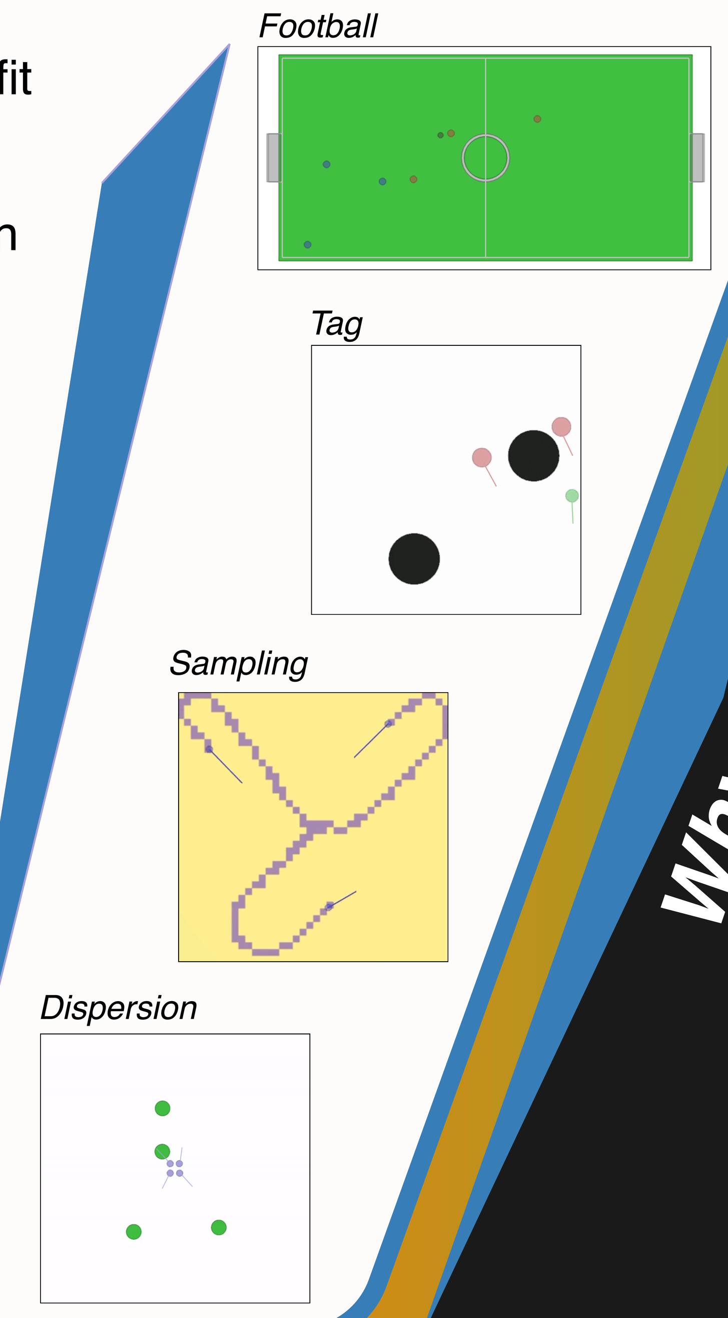
**Diversity** has been shown to be **key to collective intelligence** in both natural and artificial systems.

Despite this, **existing approaches either do not consider diversity or blindly boost it by using**:

- Intrinsic rewards
- Additional loss functions

Thus effecively modifying the learning objective and having no principled measure for it.

***We introduce** Diversity Control (DiCo), **the first method able to control diversity to an exact value** or range of a given metric **without changing the learning objective.***




## TL;DR

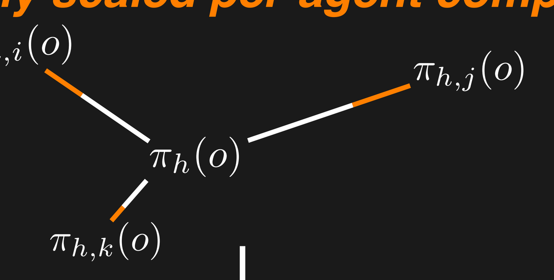
***Diversity is key*** to collective intelligence

Existing approaches promote it blindly via:

- Intrinsic rewards
- Additional loss functions

We introduce ***Diversity Control (DiCo)***, the first method method ***to control diversity with no additional learning objective***

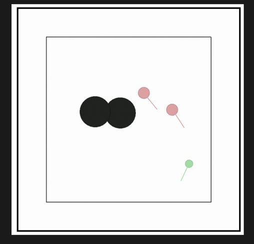
We do this by representing policies as the sum of a ***parameter-shared component*** and ***dynamically scaled per-agent components***



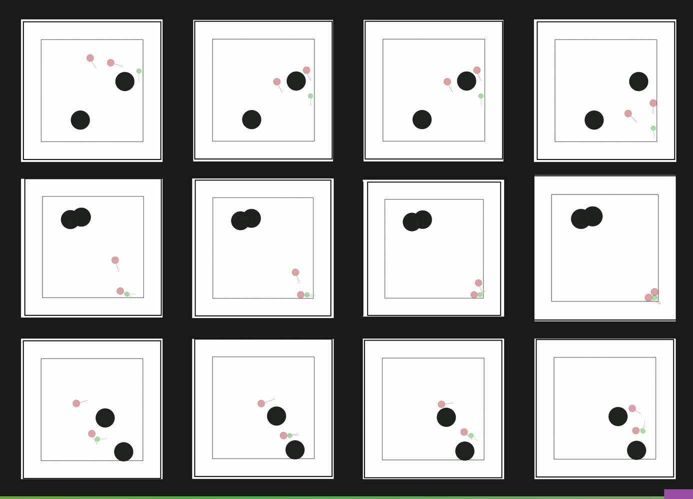

We provide theoretical proofs and demonstrate it empirically in a didactic ***case study***

Our experiments show how DiCo can betemployed to ***boost performance and sample efficiency in MARL***

In predator-prey tasks, where homogeneous and unconstrained heterogeneous predators all blindly chase after the prey



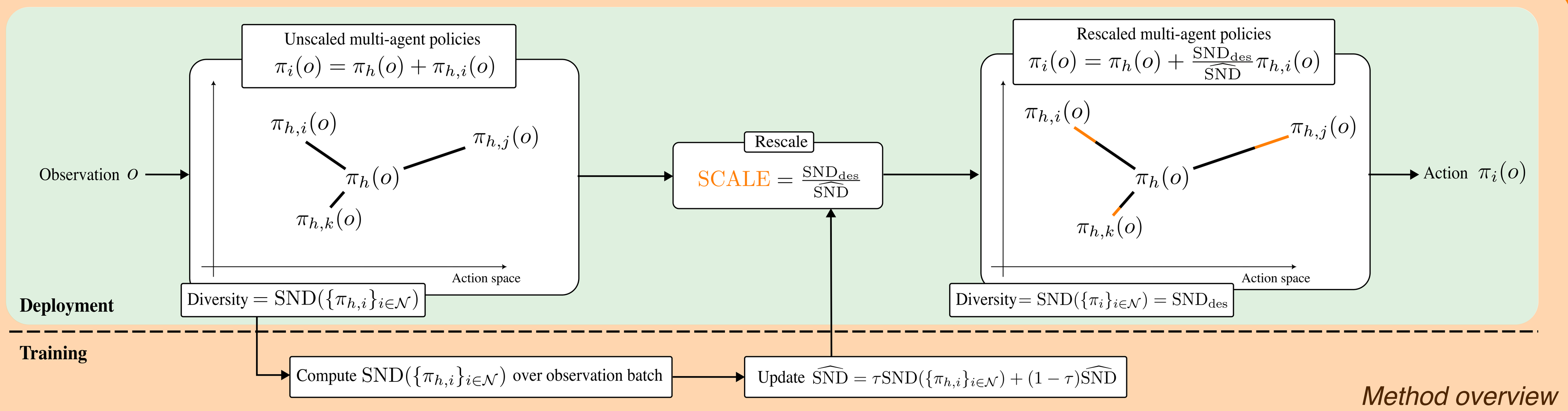
***DiCO finds emergent diverse strategies***




Why care? · Method · Case study · Experiments

## Method

### Dynamically rescaling policies



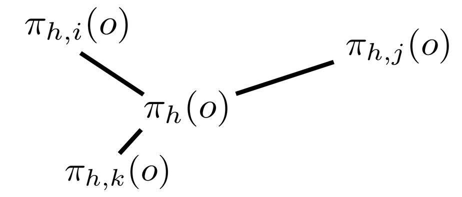

*Method overview*

We use System Neural Diversity $\mathrm{SND}(\{\pi_i\}_{i\in\mathcal{N}})$ to measure behavioral diversity

### *Divesrity Control (DiCo)*

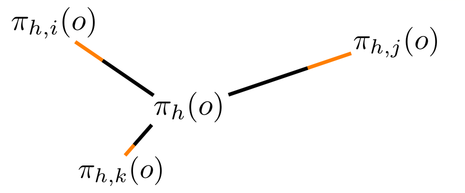
1. We represent multi-agent policies as a **heterogeneous deviations** $\pi_{h,i}(o)$ from a **homogeneous reference** $\pi_h(o)$

$$\pi_i(o) = \pi_h(o) + \pi_{h,i}(o)$$




2. Policies are then **rescaled dynamically** wrt the homogeneous reference given the **desired diversity** $\mathrm{SND}_{\mathrm{des}}$ and their **current diversity** $\widehat{\mathrm{SND}}$

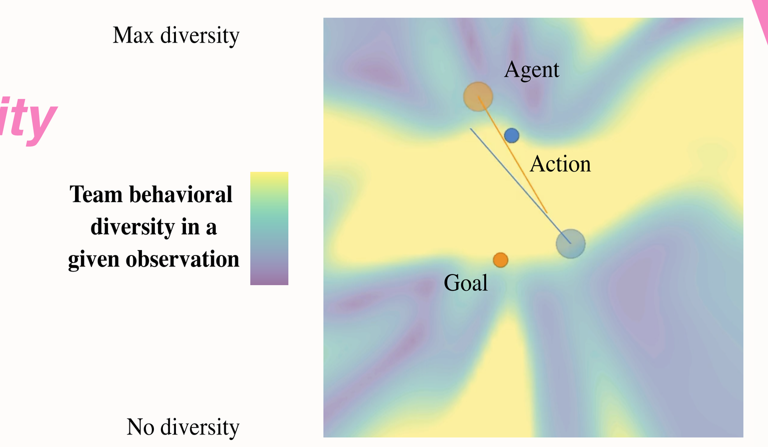
$$\pi_i(o) = \pi_h(o) + \frac{\mathrm{SND}_{\mathrm{des}}}{\widehat{\mathrm{SND}}}\pi_{h,i}(o)$$



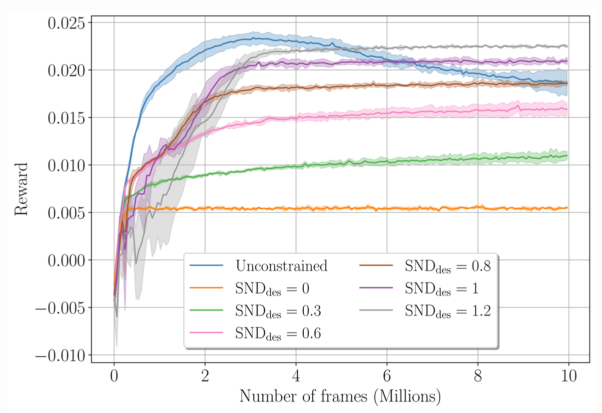

## Case study

### A simple example of controlling diversity

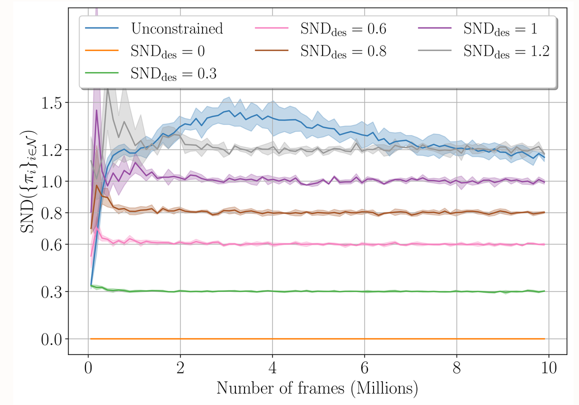
We demonstare our method in a **Multi-Agent Navigation** task, where each **agent observes all goals and has to navigate to a specific one.** Thus, agents **need to be diverse** to go to different goals.

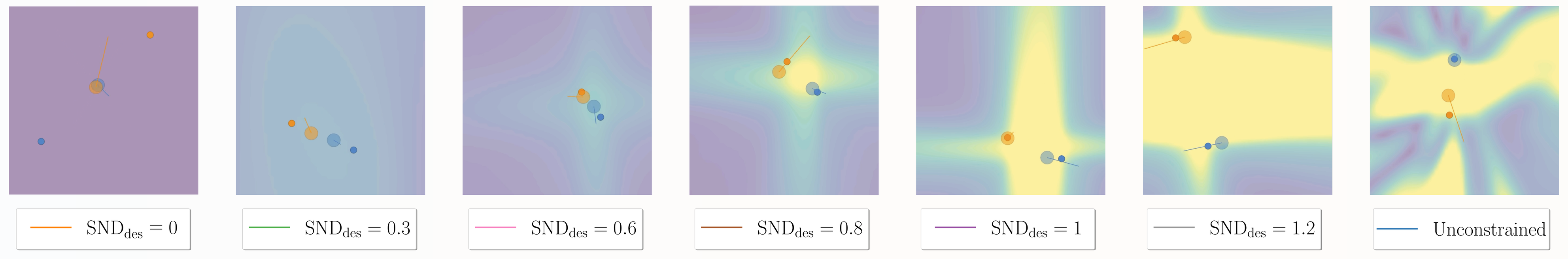



Reward




Diversity




## Experiments

### Improving MARL sample efficiency and performance

We run experiments, in **cooperative and competitive** tasks, that show how DiCo can be employed as a novel paradigm to **increase performance** and sample efficiency.

By controlling diversity, we can search the beahvioral space at different heterogeneity levels, leading to the **emergence of novel strategies** not found by unconstrained agents.

*Agents constrained with high diversity find better policies.*

*Unconstrained diverse agents settle to lower diversity*