Decentralized MCTS via Learned Teammate Models

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Abstract

A key difficulty of cooperative decentralized planning lies in making accurate predictions about the decisions of other agents. In this paper we present a policy improvement operator for learning to plan in iterated cooperative multi-agent scenarios. At each application of our method, a selected agent learns an approximation of policies of its teammates from data from past simulations. Under the assumption of ideal function approximation, successive iterations of our algorithm are guaranteed to improve the policies, and eventually lead to convergence to a Nash equilibrium in a coordinate ascent manner. We combine the policy improvement operator with the decentralized Monte Carlo Tree Search planning method and demonstrate the application of the algorithm on several scenarios in the spatial task allocation problem introduced in [Claes *et al.*, 2015]. We show that deep learning and convolutional neural networks can be efficiently employed to produce policy approximators which exploit the spatial features of the problem, and that the proposed algorithm improves over the baseline planning performance for particularly challenging domain configurations.

1 Introduction

The ability to compute or learn plans to realize complex tasks is a central question in artificial intelligence. However, in the case of multiagent systems, most such techniques assume a offline, centralized phase in which this planning or learning takes place [Oliehoek, 2012; Foerster *et al.*, 2018], such that merely the execution of these found plans is decentralized. This stands in stark contrast to human collaboration: in most context we plan individually, and in parallel with other humans. For instance, a shopkeeper and a customer do not sit down to jointly plan when to do the restocking and shopping. As such, the development of such decentralized planning methodologies is of critical importance if we are interested in replicating and understanding human-like intelligence. Moreover, decentralized planning method can lead to a number of benefits, such as robustness, reduced computational load and absence of communication overhead [Claes *et al.*, 2017].

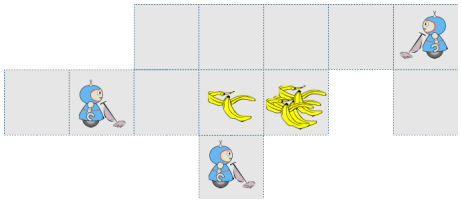


Figure 1: Robots cleaning a factory floor.

Some succesful approaches to decentralized planning were studied in context of multiplayer computer games [Jaderberg *et al.*, 2019], robot soccer [Aşık and Akın, 2012], intersection control [Vu *et al.*, 2018] and autonomous warehouse control [Claes *et al.*, 2017], to name a few. The difficulty of decentralized planning lies in solving the coordination problem. To naively deploy single-agent algorithms for individual agents inevitably leads to the tragedy of the commons; i.e. a situation where an action that seems optimal from an individual perspective, is suboptimal collectively. For instance, consider a relatively simplistic instance of a spatial task allocation problem in which a team of n robotic vacuum cleaners needs to clean a factory floor, as in Figure 1. Assuming that a robot solves its own traveling salesman problem [Lin, 1965] would result in optimal path planning if it was alone in the factory; but collectively it could lead to unnecessary duplication of resources with multiple robots heading to the same littered area. On the other hand, joint optimization of all actions results in an intractable problem, that is not scalable to large networks of agents. Among some of the heuristic methods to deal with such problems proposed by researchers, communication [Wu *et al.*, 2009], higher level coordination orchestration [Borrajo and Fernández, 2019] and co-agent modelling [Albrecht and Stone, 2018] were previously explored in literature.

The optimal decentralized planning question can be posed in different settings; within this paper we focus on *simulation-based planning*, where agents have access to the simulator of the environment, which they can use to sample states and rewards, and evaluate the value of available actions, before committing to a particular one. The inherent difficulty of decentralized simulation-based planning is that in order for

an individual agent to sample from the simulator and estimate the potential future rewards, it needs to provide *joint actions* of themselves and their teammates. However, in a live planning scenario, where each of the agents chooses actions according to their own simulation-based algorithm, it is not possible to know *a priori* what actions teammates actually execute. If all agents are deployed with the same algorithm, they can evaluate all joint actions and choose their respective individual action; however this approach is costly, when performed online, and the computational difficulty grows exponentially with the number of agents.

A different approach is to make assumptions on other agents, and supply the simulator with an educated guess on their actions, given the common observed state. Such solution was used in [Claes *et al.*, 2017], where heuristic policies were designed for a domain modelling the task allocation problem in a factory floor. [Doshi and Gmytrasiewicz, 2009] employed particle filters to emulate nested reasoning sequences; this method came with performance improvement guarantees, however in practice the performance was limited by the computationally achievable depth of the nested modelling.

In this paper we combine the best of both approaches. We introduce a decentralized planning method of *Alternate maximization with Behavioural Cloning* (ABC). Our algorithm combines the ideas of alternate maximization, behavioral cloning and Monte Carlo Tree Search (MCTS) in a previously unexplored manner. By the ABC method, the agents learn the behavior of teammates, and adapt to it in an iterative manner. We use neural networks to learn models of teammate behaviour, and employ them iteratively, creating a policy improvement operator. Contrary to [Claes *et al.*, 2017], our method is domain independent, but at the same time does not require the extensive computational power of nested planning as in [Gmytrasiewicz and Doshi, 2005]. The proposed policy improvement process is designed to follow the hill climb principle, where only one agent adapts at a time; In particular, we prove that under perfect learning conditions, we are guaranteed to increase the mean total reward at each step, and eventually converge to a Nash equilibrium.

1.1 Related work

In addition to the papers we previously discussed, we would like to mention several other decentralized MCTS methods that are related, but different to our work. In [Kurzer *et al.*, 2018] decentralized MCTS is combined with macro-actions for automated vehicle trajectory planning. The authors however assume heuristic (so not always accurate) models of other agents and do not learn their actual policies. [Best *et al.*, 2016] uses parallel MCTS for an active perception task and combines it with communication to solve the coordination problem. Contrary to them, we assume no communication during the execution phase. Similarly, [Golpayegani *et al.*, 2015] uses MCTS in a parallel, decentralized way, but includes a so-called Collaborative Stage at each decision making point, where agents can jointly agree on the final decision. In [Amato and Oliehoek, 2015] a factored structure of the environment transitions was exploited to decouple the planning process. In our setting, we do not make any assumptions about the dynamics of the environment.

Finally, we would like to point out similarity of our approach with AlphaGo & AlphaZero – the computer programs designed to master the game of Go in a highly acclaimed research by Deepmind [Silver *et al.*, 2016] There, neural network models were used together with self-play to guide the Monte Carlo Tree Search, by providing guesses of opponents gameplay and estimates on state-action value functions. However, both AlphaGo & AlphaZero needed to expand the opponents actions in the search tree. By our approach, we are able incorporate the actions of other agents in the environment simulator, which vastly reduces the branching factor of the tree and allows to scale the method to more than two agents.

2 Background

2.1 Multiagent Markov Decision Processes

A Markov Decision Process (MDP) is defined as a 5-tuple $M := (S, A, T, R, \gamma)$, where S is the finite set of states, A is the finite set of joint actions, $T : S \times A \times S \to [0, 1]$ are the probabilities of transitioning between states for particular choices of actions, $R : S \times A \times S \to \mathbb{R}$ is the reward function, and $\gamma \in [0, 1]$ is the discount factor. The *policy* is a mapping $\pi : S \to A$, which represents an action selection rule for the agent. The policy is paired with the environment to form a Markov chain over the state space defined by the sequence of probability distribution functions which models the process of decision making, The value of a state is given by

$$V^{M,\pi}(s_0) = \sum_t \gamma^t \mathbb{E}(R_t|\pi, s_0) \tag{1}$$

One is typically interested in finding the *optimal policy*, $\pi^* := \operatorname{argmax}_\pi V^\pi$. The value of action a in a given state s is given by the Q function

$$Q^{M,\pi}(s, a) := R(s, a) + \gamma \sum_{s'} T(s'|s, a) V^{\pi^*}(s'). \tag{2}$$

By the Bellman optimality principle, the actions with highest Q values form the optimal policy $\pi^*(s, a) = \operatorname{argmax}_{a \in A} Q(s, a)$.

A Multi-agent Markov Decision Process (MMDP) on n agents the action space is factored in n components: $A = A_1 \times \cdots \times A_n$. Each component A_i describes the individual actions available to the agent i and the policies can be represented as products of individual agent policies $\pi = (\pi_1, \ldots, \pi_n)$. For our considerations, it will be useful to introduce the i-th self-absorbed projection of the MMDP $M = (S, A, T, R, \gamma)$, after having fixed all individual policies besides π_i, as a single agent MDP:

$$\Pi_i(M, \pi_{-i}) := (S, A_i, T_i, R_i) \tag{3}$$

where π_{-i} denotes (fixed) policies of all agents except for agent i and the transitions and rewards are induced by combining T, R with π_{-i}.

The problem of finding solutions to an MMDP can be viewed as a collaborative normal form game [Claus and Boutilier, 1998; Peshkin *et al.*, 2000], where the agents are

players, the individual policies are strategies, and the payoffs for a joint policy π and an initial state s_0 are given by $V^{\pi}(s_0)$, and uniform to all players. A joint policy is a *Nash equilibrium* if and only if no higher payoff can be achieved by changing only one of the individual policies forming it. The optimal policy $\pi^{*,M}$ is a Nash equilibrium, however there may be multiple other (possibly suboptimal) Nash equilibria in the system.

2.2 Multi-agent planning in MMDPs

The question of finding an optimal joint policy can be considered in the simulation-based planning context. There, it is no longer assumed that we have access to the full probabilistic model of the domain. Instead, one is supplied with a *system simulator*, i.e. a method for sampling states s' and rewards r based on states s and joint actions a, according to the underlying (but otherwise possibly unknown) probability distribution T and reward function R. In this paper, we consider the setting of online, decentralized, simulation-based planning, where the individual agents need to compute individual best responses $\pi_i^*(s)$ states $s \in S$ they encounter in the episode.

We focus on one particularly effective and popular planning method: the Monte-Carlo Tree Search (MCTS) algorithm combined with the Upper Confidence Trees (UCT) tree exploration policy. MCTS is a heuristic search algorithm which uses Monte Carlo simulations to construct a tree of possible future evolutions of the system. The tree consists of nodes representing actions taken by the agent, and the resulting, sampled states encountered in the environment. Each node stores statistics that approximate either the state values or the Q values of actions. The single iteration of algorithm execution is split into four parts. First, the tree is traversed according to the tree policy (selection). Then, new nodes are created by sampling an action and the resulting state (expansion). Next, a heuristic policy is used to complete the episode simulation (rollout). Finally, the results are stored in the visited tree nodes (backpropagation).

The selection of an action node k by the UCT algorithm is given by the formula $\tilde{Q}(s,a,t) + c\sqrt{\frac{\log N_k}{n_k}}$, where $\tilde{Q}$ is a sample-based estimator of the Q value, N_k is the amount of visits at the parent node of node k, and n_k is the amount of visits of node k. All of these three values are updated at each backpropagation step. The constant $c > 0$ is the exploration constant; in theory, for rewards in $[0,1]$ range, it should be equal to $\sqrt{2}$. In practice the constant is chosen empirically [Kocsis and Szepesvári, 2006].

The algorithm is initialized and performed at each time step of simulation for either a predefined or time-limited amount of iterations, and then the best action is selected greedily, based on the approximate Q-values of child nodes of the root node.

Definition 1. *We denote the policy generated by action selection according to the MCTS algorithm with UCT in an MDP M by $MCTS(M)(= MCTS(M,C,l,\rho))$, with $C > 0$ being the exploration constant, $l \in \mathbb{N}$ the number of UCT iterations and ρ – a rollout policy.*

For a sufficiently large number of iterations $l = l(C,M)$ the MCTS algorithm approximates the real Q-values of each action node with arbitrary accuracy; and therefore it constitutes the pure, optimal policy: $MCTS(M,C,l,\rho) = \pi^{*,M}$, c.f. [Chang *et al.*, 2005].

3 Alternating maximization with Behavioral Cloning

3.1 The hill climb method

A common method for joint policy improvement in multi-agent decision making is the so-called *hill climb*, where agents alternate between improving their policies (c.f. [Nair *et al.*, 2003]). At each iteration of the method, one of the agents is designated to compute its best response, while the other agents keep their policies fixed. The hill climb method comes with performance guarantees, in particular the joint rewards are guaranteed to (weakly) increase after each iteration.

Consider an MMDP on n agents $M = (S,A,T,R)$, and let $(\pi_1,\ldots,\pi_n)$ denote the individual components of a joint policy π.

Definition 2. *For each $i \in \{1,\ldots,n\}$ we define the i-th best response operator BR_i from the joint policy space to itself by:*

$$BR_i(\pi) := \left(\pi_1,\ldots,\pi_{i-1},\pi_i^{*,\Pi_i(M,\pi_{-i})},\pi_{i+1},\ldots,\pi_n\right). \tag{4}$$

Lemma 1. *The following inequality holds:*

$$V^{M,BR_i(\pi)}(s) \geq V^{M,\pi}(s),\ \forall s. \tag{5}$$

Moreover, $V^{M,BR_i(\pi^0)}(s) = V^{M,\pi^0}(s)$ implies that π^0 is a fixed point of BR_i.

Proof. For all $s \in S$:

$$\begin{aligned} V^{M,BR_i(\pi)}(s) &= V^{\Pi_i(M,\pi_{-i}),(BR_i(\pi))_i}(s) \\ &= V^{\Pi_i(M,\pi_{-i}),\pi_i^{*,\Pi_i(M,\pi_{-i})}}(s) \\ &\geq V^{\Pi_i(M,\pi_{-i}),\pi_i}(s) \\ &= V^{M,\pi}(s). \end{aligned} \tag{6}$$

The inequality is strong iff $\pi_i \neq \pi_i^{*,\Pi_i(M,\pi_{-i})}$. □

Applications of lemma 1 to simulation-based planning can seem counter-intuitive, and very much in spirit of the aphorism *all models are wrong, but some are useful*:

Remark 1. *Consider the following composition $BR_i(BR_j(\pi))$ with $i \neq j$ for some joint policy π; the interpretation is that agent j first adapts to the policies π_{-j}, including the i-th agent's policy π_i; then agent i adapts to the policies $(BR_j(\pi))_{-i}$. The application of operator BR_i on $BR_j(\pi)$ means that agent i possibly changes its own policy, which causes agent j to act upon a false belief. Nevertheless, the value of the joint policy still increases.*

Definition 3. *Let σ be a permutation on the set $\{1,\ldots,n\}$. We define the joint policy operator by $JR_\sigma := T_{\sigma(n)} \circ \cdots \circ T_{\sigma(1)}$.*

Corollary 1. *For all permutations σ and all initial joint policies the iterative application of operator JR_σ converges to a Nash equilibrium. Since the policy space is finite, the convergence is achieved in finite time.*

Proof. To make the argument easier to follow, we will assume that $\sigma = \mathrm{id}$, and denote JR_{id} as JR. For the purpose of this proof we denote the N-th composition of JR by JR^N, for any $N \in \mathbb{N}$. Since $V^{M,JR(\cdot)}(s)$ is non-decreasing as a function of joint policies, and the policy set is finite, for any joint policy π there exists an $N \in \mathbb{N}$ such that $V^{M,JR^{(N+1)}(\pi)}(s) = V^{M,JR^N(\pi)}(s)$. We will show that $\pi^N := JR^N(\pi)$ is a Nash equilibrium. Since V increases along trajectories generated by BR_i, we have

$$V^{M,JR^N(\pi)}(s) = V^{M,BR_1(JR^N(\pi))}(s)\ \forall s \tag{7}$$

and by the second part of Lemma 1

$$BR_1(JR^N(\pi)) = JR^N(\pi). \tag{8}$$

By an inductive argument

$$BR_i(JR^N(\pi)) = JR^N(\pi). \tag{9}$$

for all $i \in \{1, \ldots, n\}$, which concludes the proof. □

3.2 Behavioral cloning

In an online planning setting, accessing the policies of other agents can be computationally expensive, especially if the policies of individual agents are formed by executing an algorithm which evaluates the Q values "on-the-go" – such as in MCTS. To address this issue, we propose to use machine learning models.

More precisely, we divide our policy improvement process into generations; at each generation we update models in the simulator of one of our agent's with samples of other agents policies from the previous generations. Through machine learning we are able to extrapolate and to give predictions of actions for states that were unseen during the previous simulation runs (e.g. were never explored by the policies of previous generations). By our method each agent i uses MCTS to conduct its own individual planning in the environment $\Pi_i(M, \pi^h_{-i})$. Therefore, the planning is fully decentralized, and no communication is needed to execute the policies.

3.3 The ABC pipeline

Our policy improvement pipeline based on MCTS is presented in pseudocode in Algorithm 1. The behavioral cloning algorithm is presented in pseudocode in Algorithm 2.

Since MCTS with UCT converges to actual Q values, we can conclude that for sufficient number of iterations our algorithm indeed executes the best responses to the assumed policies:

Corollary 2. *Let π^g be as in Algorithm 1. For l large enough $\pi^g_i = \pi^{*,\Pi_i\left(M,\pi^{h,g-1}_{-i}\right)}$, and as consequence $\pi^g_i = BR_i(\pi^{h,g-1}_{-i})$.*

If our machine learning model has enough data and expressive capacity to perfectly replicate policies, based on Lemma 1 and Corollary 1 we conclude that the procedure improves joint policies and eventually converges to a Nash equilibrium:

Initialization;
environment M;
initial heuristic policies $\pi^{h,0} = (\pi^{h,0}_1, \ldots, \pi^{h,0}_n)$ to model agents in MCTS;
MCTS parameters l, C, p;
MCTS policies $\pi^0 = (\pi^0_1, \ldots, \pi^0_n)$:
$\pi^0_i := MCTS\left(\Pi_1(M, \pi^{h,0}_{-i}), l, C, \pi^{h,0}_{-i}\right)$;
for *g in 1:nGenerations* **do**
  set the policies π^g_i of agents $i = 1, \ldots, n$ by;
  $\pi^g_{g \bmod n} :=$
  $\mathrm{MCTS}\left(\Pi_{g \bmod n}\left(M, \pi^{h,g-1}_{-(g \bmod n)}\right), l, C, p, \pi^{h,g-1}_{g \bmod n}\right)$;
  $\pi^g_{-(g \bmod n)} := \pi^{g-1}_{-(g \bmod n)}$;
  collect state-action data d from $nSim$ simulations of the domain M with agents π^g_i;
  train policies $\pi^{h,g} \approx \pi^g$ by Algorithm 2 with data d;
end

Algorithm 1: The ABC policy improvement pipeline.

intialization Data $d = (s^g_i, a^g_i)_{i,g}$ of state-action pairs indexed by agent g;
neural network policy models $\pi^h_g(\theta_0, \cdot)$ with softmax output over action space;
for *g in 1:nAgents* **do**
  Convert states s^g_i to arrays;
  One-hot-encode actions a^g_i;
  Initialize neural network policy approximators with weights $\theta := \theta_0$;
  for *n in 1:nTrainingEpochs* **do**
    draw batch B_g ;
    minimize $-\sum_{(s^g_i, a^g_i) \in B_g} a^g_i \log(\pi^{h,g}(\theta, s)))$ over θ (cross-entropy);
  end
end

Algorithm 2: The algorithm for training of policy approximators.

Theorem 1. *For a large enough values of l and under assumption $\pi^{h,g} = \pi^g$, $\forall g$, the joint policy value $V^{\pi^g,M}(s_0)$ is non-decreasing as a function of g, and strongly increasing until it reaches the Nash equilbrium. For N large enough, π^N is a Nash equilibrium.*

We emphasize that it is essential that only one agent updates its assumed policies at each generation. If two or more agents would simultaneously update their policies, they could enter an infinite loop, always making the wrong assumptions about each other in each generation, and never achieving the Nash equilibrium.

4 Experiments

Since our work is a natural extension to [Claes *et al.*, 2015; Claes *et al.*, 2017], we perform experiments on a slightly modified version of the Factory Floor domain introduced

therein. The baseline for our experiments is given by individual MCTS agents with heuristic models of other agents [Claes *et al.*, 2017], and also serves as initialization (generation 0) of the ABC policy iterator. Therefore, the goal of the experiments is to empirically confirm the policy improvement via ABC. Any improvement over the 0th generation shows that we have managed to beat the baseline.

4.1 Problem domain

For our experiments we use a slightly modified version of the Factory Floor domain previously employed in [Claes *et al.*, 2015; Claes *et al.*, 2017]. The domain consists of a gridworld-like planar map, where each position can be occupied by (cleaning) robots and tasks (e.g. litter). Multiple robots and/or tasks can be in the same position. Each robot is controlled by an agent, and at each time step an agent can perform either a movement action $UP, DOWN, LEFT, RIGHT$, which shifts the position of the robot accordingly, or a cleaning action ACT, which removes one task at the current position. Attempted actions may succeed or not, according to predefined probabilities. The reward collected at each time step is the number of tasks cleaned by the robots. At the beginning of the simulation there can already be some tasks on the map, and as simulation progresses at each time step a number of tasks can be added to the map according to predefined probabilities.

4.2 Initial heuristic models

Below, we describe the heuristic policy of agent i $\pi_i^{h,0}$, which is supplied as the model for MCTS agents in generation 0 (the baseline). At each step the agent performs the following steps:

1. it computes the *social order* of the corresponding robot among all robots sharing the same position; the social ordering function is predefined by the lexicographic order of unique robot identifiers.
2. It evaluates each possible destination τ by the following formula:

$$NV(\tau, \text{robot}_i) = \begin{cases} -\infty \text{ if no tasks at } \tau, \\ \frac{\#\text{tasks}}{\text{dist}(\tau, \text{robot}_i)}; \end{cases} \quad (10)$$

3. It assigns the k-th best destination as the target destination, where k is the computed social order of the corresponding robot (e.g. if it is the only robot at a given position, then $k = 1$). Therefore, the social order is used to prevent several agents choosing the same destination.
4. It chooses action ACT if it is already at the target destination; and otherwise it selects a movement action along the shortest path to the destination.

4.3 MCTS settings

We scale the exploration constant C by the remaining time steps in the simulation, i.e. $c = c(t) := C * (H - t)$, to account for the decreasing range of possible future rewards, as recommended in [Kocsis and Szepesvári, 2006]. As in the baseline, we also use sparse sampling to combat the problem of large state space; that means that we stop sampling child state nodes of a given action node from the simulator after we have sampled p times; instead we sample the next state node from the existing child state nodes, based on frequencies with which they occured. In all our experiments, p is set to 20. As in the baseline, the agents are awarded an additional do-it-yourself bonus of 0.7 in simulation, if they perform the task themselves; this incentivizes them to act, rather than rely on their teammates. Each agent performs 20000 iterations of UCT to choose the best action for their robot.

4.4 The behavioral cloning model

Since the domain has spatial features, we opted to use a convolutional neural network as the machine learning method of choice for policy cloning.

As input we provide a 3-dimensional tensor with the width and the height equal to the width and the height of the Factory Floor domain grid, and with $n + 2$ channels (i.e. the amount of robots plus two). We include the current time step information in the state. The 0-th channel layer is a matrix filled with integers representing the amount of tasks at a given position. The tasks have finite execution time, and the current time step affects the optimal decision choice; therefore we encode the current time step by filling it in the entries of the 1st channel. Finally, for $i = 1, \ldots, n$, the $2 + i$-th channel is encoding the position of robot i, by setting 1 where the robot is positioned and 0 on all other fields.

Such state representation is fed into the neural network with two convolutional layers of 2x2 convolutions followed by three fully connected layers with 64, 16 and 5 neurons respectively. We use the rectified linear unit activation functions between the layers, except for the activation of the last layer, which is given by the softmax activation function. The network has been trained using the categorical cross entropy function as the loss function, and Adam as the optimization method [Kingma and Ba, 2014]. The action assigned to the state during MCTS simulations is corresponding to the argmax coordinate of the softmax probabilities.

4.5 Domain initialization

We tested our method on four domain configuration. In all subdomains, the movement actions are assumed to succeed with probability 0.9, and the ACT action is assumed to succeed always. In both configurations the horizon H is set to ten steps. We present the initial configuration of the experiment and the corresponding reward curves in Figures 2, 3 4. The letter R indicates the robot positions, and the numbers indicate the amount of tasks at a given position – for a fixed task placement, or the probability that a task appears at a given position – for dynamic task placement. We provide plots of the results, that contain the mean average episode reward of simulations of each generation, together with 95% confidence interval bars.

We chose domain configurations which, due to the location of tasks require high level of coordination between agents. In particular, we created the domains where we expect that the policies of the baseline are suboptimal. For more generic domains explored therein, the decentralized MCTS with heuristic models is already close to optimal, and we do not expect much improvement. In subdomains with fixed positions of

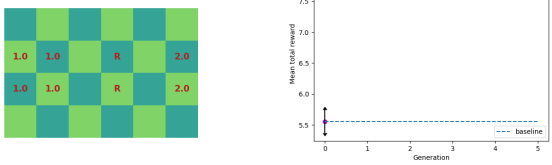


Figure 2: Left: The two robots experiment map. Right: Mean rewards of the experiment with two robots. Each generation represents 320 simulations.

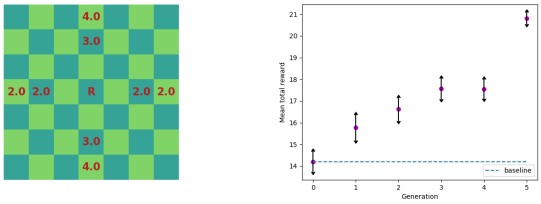
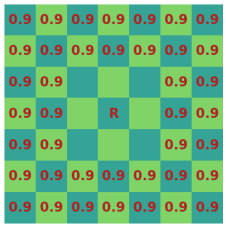


Figure 3: Left: The four robots experiment map with fixed task allocation. All robots start in the middle. Right: Mean rewards of the four robots experiment with fixed task positions. Each generation represents 180 simulations.

tasks we train the agents for 5 generations. In subdomains, where the tasks are assigned dynamically, we train the agents for 3 generations, as for higher amount of iterations we sometimes observed worsening performance, which we attribute to imperfect learning process due to high stochasticity of the domain.

Two robots Our first subdomain is a trivial task: a 6x4 map which has 8 tasks to be collected. Even in such simple scenario, the baseline does not perform well, because both robots make the assumption that their colleague will serve the task piles of 2's and head for the 1s, achieving a mean reward of ≈ 5.5 (0th generation). The exploration parameter C is set to 0.5, and the number of simulations at each generation $nSim$ to 320. Already in the first generation, agent 2 learns the policy of agent 1 and adapts accordingly, which results in an increase of the mean collected reward to ≈ 7.9. The average collected reward stabilizes through the next generations, which suggests that our method reached a Nash equilibrium (and in fact a global optimum, given that the maximal reward that could have been obtained in each episode is 8).

Four robots, fixed tasks Our second subdomain is a 7x7 map which has 22 tasks to be collected by four robots. The exploration parameter C is increased to 1.0 – to account for higher possible rewards, and the number of simulations at each generation $nSim$ is decreased to 180 – to account for longer simulation times. All robots start from the middle of the map. The baseline method again underpeforms, as the robots are incentivized to go for the task piles of 3's and 4's, instead of spreading in all four directions. After the application of the ABC algorithm the robots learn the directions of their teammates, spread, and a near optimal learning performance is achieved, see Figure 3.



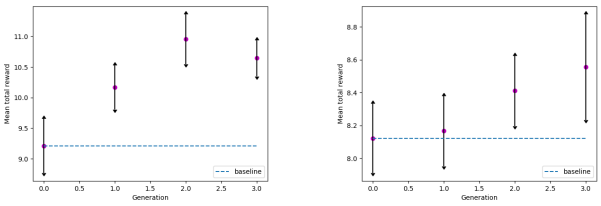


Figure 4: Top: the four robots experiment map with dynamic task allocation. All the robots start in the middle. Bottom: Mean rewards of the dynamic task assignment experiment with four robots and two (left) / three (right) tasks appearing at each time step – data from 90/180 simulations respectively.

Four robots, dynamic tasks For the final two experiments we chose the same 7x7 map as previously, but this time tasks appear dynamically: two or three new tasks are added randomly with probability 0.9 at each time step during the program execution in one of the marked places. All the other experiment parameters remain unchanged.

The confidence intervals are wider due to additional randomness. Nevertheless, for the first 3 generations we observed an improvement over the 0th generation, which we attribute to the fact that the agents have learnt that they should spread to cover the task allocation region, similarly as in the experiment with fixed task location.

5 Conclusions

We have proposed a machine-learning-fueled method of improving teams of MCTS agents. Our method is grounded in theory of alternating maximization and, given sufficiently rich training data and suitable planning time, it is guaranteed to improve the joint policies. We have shown that in practice the method allows to improve team policies for a spatial task allocation problem and domains where coordination is crucial to achieve optimal results.

An interesting direction of future work is to adapt the method for search of the global optimum of the adaptation process, rather than a local, Nash optimum. To that end, one can randomize the orded in which agents are adapting, locate multiple Nash equilibria, and select the one with highest performance. Another research direction is to extend the ABC method to environments with partial information (Dec-POMDPs), where the agents need to reason over the information set available to their teammates.

6 Acknowledgments

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