ToM2C: Target-oriented Multi-agent Communication and Cooperation with Theory of Mind

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Abstract

Being able to predict the mental states of others is a key factor to effective social interaction. It is also crucial for distributed multi-agent systems, where agents are required to communicate and cooperate. In this paper, we introduce such an important social-cognitive skill, *i.e.* Theory of Mind (ToM), to build socially intelligent agents who are able to communicate and cooperate effectively to accomplish challenging tasks. With ToM, each agent is capable of inferring the mental states and intentions of others according to its (local) observation. Based on the inferred states, the agents decide "when" and with "whom" to share their intentions. With the information observed, inferred, and received, the agents decide their sub-goals and reach a consensus among the team. In the end, the low-level executors independently take primitive actions to accomplish the sub-goals. We demonstrate the idea in two typical target-oriented multi-agent tasks: cooperative navigation and multi-sensor target coverage. The experiments show that the proposed model not only outperforms the state-of-the-art methods on reward and communication efficiency, but also shows good generalization across different scales of the environment.

1 Introduction

Cooperation is a key component of human society, which enables people to divide labor and achieve common goals that could not be accomplished independently. In particular, humans are able to form an ad-hoc team with partners and communicate cooperatively with one another (Tomasello, 2014). Cognitive studies (Sher et al., 2014; Sanfey et al., 2015; Etel & Slaughter, 2019) show that the ability to model others' mental states (intentions, beliefs, and desires), called Theory of Mind (ToM) (Premack & Woodruff, 1978), is important for such social interaction. Consider a simple real-world scenario (Fig. 1), where three people (Alice, Bob and Carol) are required to take the fruits (apple, orange and pear) following the shortest path. To achieve it, the individual should take four steps sequentially: 1) observe their surrounding; 2) infer the observation and intention of others; 3) communicate with others to share the local observation or intention if necessary; 4) make a decision and take action to get the chosen fruits without conflict. In this process, the ToM is naturally adopted in inferring others (Step 2) and also guides the communication (Step 3).

In this paper, we study the Target-oriented Multi-Agent Cooperation problem (ToMAC). In ToMAC, the agents need to cooperatively reach the goals and keep specific relations among the agents and targets. Such problem setting widely exists in real-world applications, *e.g.* collecting multiple objects (Fig. 1), navigating to multiple landmarks (Lowe et al., 2017), monitoring a group of pedestrians (Xu et al., 2020). While running, each agent is required to choose a subset of interesting targets and reach them to contribute to the team goal. In this case, the key to realizing high-quality cooperation is to **reach a consensus among agents** to avoid the inner conflict in the team. However, the existing multi-agent reinforcement learning methods still do not handle it well, as they only implicitly model others in the state representation and are inefficient in communication.

Here we propose a **Target-oriented Multi-agent Communication and Cooperation mechanism (ToM2C)** using Theory of Mind, shown as Fig. 2. In ToM2C, each agent is of a two-level hierarchy. The high-level policy (planner) needs to cooperatively choose certain interesting targets as a sub-goal to deal with, such as tracking certain moving objects or navigating to a specific landmark. Then low-level policy (executor) takes primitive actions to reach the selected goals for k steps. To be more specific, each agent receives local observation of targets, and estimates the local observation of others in the ToM Net. Combining the observed and inferred states, the ToM net will predict/infer the target choices (intentions) of other agents. After that, each agent decides 'whom' to communicate with

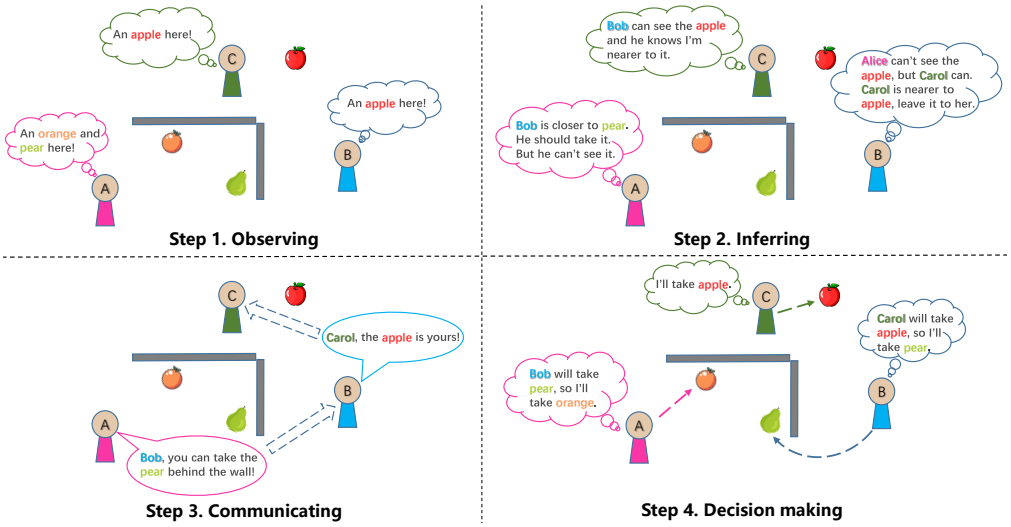


Figure 1: A fruits collection example. The agents are required to cooperatively collect the three target objects (apple, pear, and orange) in the room as fast as possible. The whole process can be divided into 4 steps. In the first step, 3 agents observe the environment and obtain the state of the visible targets. In the second step, each agent tries to infer what other agents have seen, and which targets they shall choose as goals. In the third step, each agent decides whom to communicate with according to the previous inference. In the fourth step, each agent decides its own goal of target based on what it observed, inferred, and received.

according to local observation filtered by the inferred goals of others. The message is the predicted goals of the message receiver, inferred by the sender. In the end, all the agents decide their own goals by leveraging the observed, inferred, and received information. With the inferring and sharing of intentions, the agents can easily reach a consensus to cooperatively adjust the target-agent relations.

Furthermore, we also introduce a communication reduction method to remove the redundant message passing among agents. Thanks to the centralized training decentralized execution (CTDE) paradigm, we measure the effect of the received messages on each agent, by comparing the output of the planner with and without messages. Hence, we can figure out the unnecessary connection among agents. Then we train the connection choice network to cut these dispensable channels in a supervised manner. Eventually, ToM2C systemically solves the problem of 'when', 'who' and 'what' in multi-agent communication, providing a compact, efficient and interpretable communication protocol.

The experiments are conducted in a challenging multi-sensor multi-target covering scenario. The team goal of the sensors is to adjust their orientation to cover as many targets as possible. It is shown that our method achieves the highest coverage rate among the SOTA MARL methods, e.g., I2C (Ding et al., 2020), HiT-MAC (Xu et al., 2020) and TarMAC (Das et al., 2019). Moreover, we also show good scalability of ToM2C in different populations of sensors and targets and conduct an ablation study to evaluate the contribution of each key component of our model. To demonstrate our framework in other target-oriented multi-agent cooperation tasks, we further evaluate it in the cooperative navigation scenario and achieve competitive results against existing methods.

Our contributions can be summarized in three-folds: 1) We introduce a cognition-inspired social agent with the ability to infer the mental states of others. Such ability enhances multi-agent cooperation in target-oriented tasks. 2) We provide a ToM-based communication mechanism, which is fully decentralized in execution. We also propose a communication reduction method to remove redundant connections among agents. 3) We conduct several experiments in a challenging multi-agent target coverage task and the cooperative navigation task, and show that our model not only outperforms the state-of-the-art MARL methods in performance and communication efficiency but also shows good scalability across scenes of different populations.

2 Related Work

Multi-agent Cooperation. The cooperation of multiple agents is crucial yet challenging in distributed systems. Agents' policies continue to shift during training, leading to a non-stationary

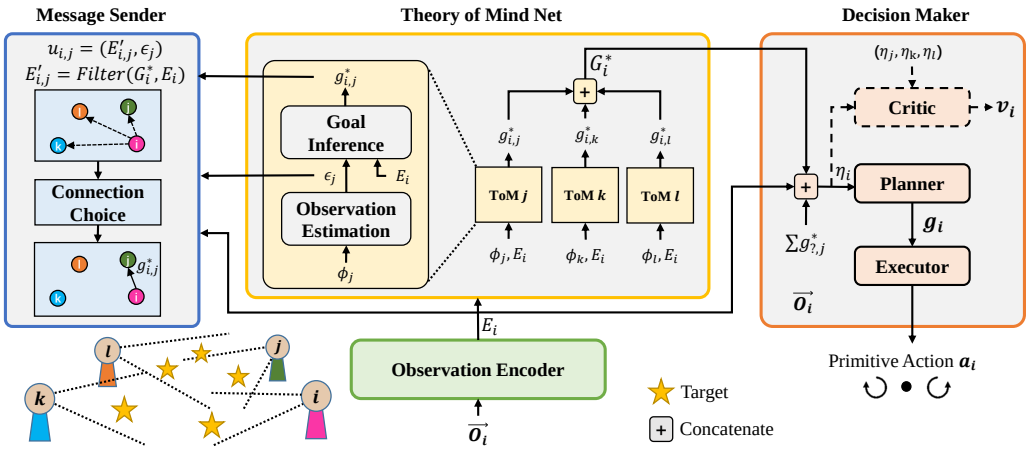


Figure 2: The architecture of ToM2C for each individual. There are 4 key components: Observation encoder, Theory of Mind net, Message sender and Decision maker. Each agent first receives a local observation and encodes it with the encoder. Then it performs Theory of Mind inference to estimate the observation of others and predict their goals. Next, it decides 'whom' to communicate with according to local observation filtered by the inferred goals of others. Finally, it makes its own decision on self goals according to what it observes, infers and receives. The low-level executor takes primitive actions to reach the chosen goals.

environment and difficulty in model convergence. Recent work (Lowe et al., 2017; Foerster et al., 2018; Sunehag et al., 2018; Rashid et al., 2018; Iqbal & Sha, 2019) in multi-agent reinforcement learning (MARL) mainly adopts centralized training decentralized execution (CTDE) paradigm to mitigate non-stationarity. However, such training method only implicitly guides agents to adapt to certain policy patterns of others. As a result, cooperation collapses in spite of a slight change in the team formation, making the model extremely impractical and poor in scalability. Furthermore, some existing work tries to make use of communication to promote cooperation, such as (Sukhbaatar et al., 2016; Das et al., 2019; Singh et al., 2019). Unfortunately, they all require a broadcast communication channel that poses a huge pressure on bandwidth. Besides, even though I2C (Ding et al., 2020) proposes an individual communication method, the message is just the encoding of observation, which is not only costly but also uninterpretable. For the target-oriented multi-agent cooperation, HiT-MAC (Xu et al., 2020) is the closest work to ours. It proposes a hierarchical multi-agent coordination framework to decomposes the target coverage problem into two-level tasks: assigning targets by the centralized coordinator and tracking assigned targets by decentralized executors. The agents in ToM2C are also of a two-level hierarchy. Differently, thanks to the use of ToM, both levels are enabled to perform distributedly.

Theory of Mind. Theory of Mind is a long-studied concept in cognitive science (Sher et al., 2014; Sanfey et al., 2015; Etel & Slaughter, 2019). However, how to apply the discovery in cognitive science to build cooperative multi-agent systems still remains a challenge. Most previous works make use of Theory of Mind to interpret agent behaviors, but fail to take a step forward to enhance cooperation. For example, Machine Theory of Mind (Rabinowitz et al., 2018) proposes a meta-learning method to learn a ToMnet that predicts the behaviors or characteristics of a single agent. Besides, Shum et al. (2019) studies how to apply Bayesian inference to understand the behaviors of a group and predict the group structure. Track et al. (2018) introduces the concept of Satisficing Theory of Mind, which refers to the sufficing and satisfying model of others. None of these works looks into the problem of multi-agent cooperation. Lim et al. (2020) considers a 2-player scenario and employs Bayesian Theory of Mind to promote collaboration. Nevertheless, the task is too simple and it requires the model of other agents to do the inference. M^{3}RL (Shu & Tian, 2019) proposes to train a manager that infers the minds of agents and assigns sub-tasks to them, which benefits from the centralized mechanism and is not comparable with decentralized methods. Wu et al. (2021) introduce Bayesian approach for ToM-based cooperation, yet assuming that the environment has a partially ordered set of sub-tasks. Above all, none of these related work has studied how to leverage ToM to guide decentralized communication and improve communication efficiency for multi-agent cooperation.

Opponent Modeling. Opponent modeling (He et al., 2016; Raileanu et al., 2018; Grover et al., 2018) is another kind of method comparable with Theory of Mind. Agents endowed with opponent modeling can explicitly represent the model of others, and therefore plan with awareness of the current status of others. Nevertheless, these methods rely on the access to the observation of others, which means they are not truly decentralized paradigms. Compared with existing methods, ToM2C applies ToM not only to explicitly model intentions and mental states but also to improve the efficiency of communication to further promote cooperation.

3 METHODS

In this section, we will explain how to build a target-oriented social agent to achieve efficient multi-agent communication and cooperation. We formulate the target-oriented cooperative task as a Dec-POMDP (Bernstein et al., 2002). The aim of all agents is to maximize the team reward. Furthermore, agents are allowed to communicate with each other to enhance cooperation. The overall network architecture is shown in Fig. 2 from the perspective of agent i. The model is mainly composed of four functional networks: observation encoder, ToM net, message sender, and decision maker. To be specific, it receives a local partial observation o_i, which includes the information of visible targets. What's more, it obtains the current pose $(\phi_1, ..., \phi_n)$ of all the agents, where n is the number of agents. The raw observation will be encoded into E_i by an attention-based encoder. Then the agent starts to do Theory of Mind inference with the ToM net. It first estimates the observation representation ϵ of each other agents according to their poses. Based on ϵ_j and E_i, agent i infers the probability of agent j choosing these targets as its goals, denoted as $G^*_{i,j}$. After that, agent i decides whom to communicate with. We employ a graph neural network here as the message sender. The node feature of agent j is the concatenation of ϵ_j and E_i filtered by $G^*_{i,j}$. The final communication connection is sampled according to the computed graph edge features. Agent i will send $G^*_{i,j}$ to agent j if there exists a communication edge from i to j. Finally, G^*_i, E_i and received messages is concatenated as η_i for planner(actor) and critic. Planner $\pi^H_i(g_i|o_i)$ is the high level policy that chooses the goals g_i, which guides the low-level executor $\pi^L_i(a_i|o_i, g_i)$ to perform primitive actions.

In the following sections, we will illustrate the key components of ToM2C in detail.

3.1 OBSERVATION ENCODER

We employ an attention module (Vaswani et al., 2017) to encode the local observation. There are two prominent advantages of this module. On one hand, it is population-invariant and order-invariant, which is crucial for scalability. On the other hand, global information can be encoded into a single feature due to the weighted sum mechanism. In this paper, we use scaled dot-product self-attention similar to (Xu et al., 2020). The local observation $\vec{o}_i$ is first transformed to key K_i, query Q_i and value V_i through 3 different neural networks. Then the output $E_i = softmax(\frac{\mathbf{Q_i}\mathbf{K_i}^T}{\sqrt{d_k}}) \odot \mathbf{V_i}$, where d_k is the dimension of one key. $\vec{o}_{i,q}$ and $\vec{E}_{i,q}$ represent the raw and encoded feature of target q to agent i respectively.

3.2 THEORY OF MIND NETWORK (TOM NET)

Inspired by the Machine Theory of Mind (Rabinowitz et al., 2018), we introduce the ToM net that enables agents to infer the observation and intentions of others. Most previous work (He et al., 2016; Raileanu et al., 2018; Lim et al., 2020) consider two-player scenarios, where the agent only needs to model one other agent. Instead, we take a step forward to evaluate our model in a more complex multi-agent scenario consisting of n(>3) agents. Therefore, the entire ToM net of agent i is actually composed of n-1 separate ToM nets, each utilized to model the corresponding agent. A single ToM net is made up of two functional modules: Observation Estimation and Goal Inference. The overall ToM net takes the poses of agents and local observation as input. Then it outputs the inferred observation and goals of others.

Observation Estimation. The first step of ToM inference is to estimate the observation representation of the other agent. The term refers to the visibility of the environment. Intuitively, when an agent tries to infer the intention of others, it should first infer which targets are seen by them. Take Bob in Fig. 1 as an example. Before he tries to infer the goals of Alice and Carol, he first infers that Alice cannot observe the apple but Carol can. Similarly, agent i infers the observation of agent j, denoted as ϵ_j, with the pose ϕ_j. Note that ϵ_j is only a representation of the observation. To better learn this representation, we introduce an auxiliary task here. Agent i needs to infer the relation between agents

and targets based on this representation ϵ_j and local observation $\vec{E}_i$. In target coverage task, agent i infers which targets are in the observation field of agent j and in cooperative navigation task it infers which landmark is closest to agent j. In practice, we employ a GRU to model the observation of others on time series.

Goal Inference. After agent i finishes the observation estimation of others, it is able to predict which targets will be chosen by them at this step. Just like humans, the agent infers the intentions of others based on what it sees and what it thinks that others see. If we denote this goal inference network as a function GI, then the process can be formulated as $G^*_{i,j,q} = GI(\vec{E}_{i,q}, \epsilon_j)$. $G^*_{i,j,q}$ stands for the probability of agent j choosing target q, inferred by i. Since there are a total of n agents and m targets in the environment, $\vec{G}^*_i \in \mathbb{R}_{(n-1)\times m}$.

Although an agent has ToM models for each of the other agents(see Fig. 2), we simply let these models be shared because all the agents are homogeneous.

With ToM net, each agent holds a belief on the observation and goal intentions of others. Such belief is not only taken into account for final self decision, but also serves as an indispensable component in communication choice. The details will be discussed in the next section.

3.3 Message Sender

Learning to communicate has been studied in a number of multi-agent reinforcement learning works. However, most of them either require a public communication channel or a centralized mechanism to decide the communication connection, which is definitely unrealistic for real multi-agent systems. Moreover, the message is usually an encoded feature, making it both uninterpretable and lengthy.

Instead, we introduce a message sender by leveraging the information inferred by ToM net. Each agent decides 'when' and with 'whom' to communicate completely on its own. And the message is the inferred ToM goals of the receiver. To achieve this, we use a graph neural network similar to Li et al. (2020); Battaglia et al. (2016). The details are in the next paragraph. After the model is trained, we further propose a communication reduction method to remove useless connections and improve communication efficiency.

Inferred-goal Filter. As stated before, we use Graph Neural Network (GNN) to learn the connection in an end-to-end manner. In previous works (Jiang et al., 2019), there is only one global graph that collects all the observations as node features. Such implementation breaks individuality. Instead, we propose a method to make use of the inferred state and intention to generate local graphs. Specifically, in the perspective of agent i, the feature of agent j is the target features filtered by the inferred goals $G^*_{i,j}$ as follows. δ is a probability threshold, which we set to 0.5 in this paper. If $G^*_{i,j,q} > \delta$, then agent i will consider target q as the goal that will be chosen by agent j.

$$E'_{i,j} = \sum_{q=1}^{m} (G^*_{i,j,q} > \delta) \cdot E_{i,q} \tag{1}$$

Then we concatenate the filtered feature $E'_{i,j}$ with the estimated observation representation ϵ_j, to form the estimated node feature $u_{i,j} = (E'_{i,j}, \epsilon_j)$. For agent i itself, $u_{i,i} = (\sum_q E_{i,q}, \epsilon_i)$, where ϵ_i is also computed by Observation Estimation module with the pose of i.

Connection Choice. For a scenario consisting of n agents, there is a total of n directed graphs $\mathcal{G} = (\mathcal{G}_1, \mathcal{G}_2, ...\mathcal{G}_n)$. $\mathcal{G}_i = (\mathcal{V}_i, \mathcal{E}_i)$ is the local graph for agent i to compute the communication connection from agent i. The vertices $\mathcal{V}_i = \{f(u_{i,j})\}$, where f is a node feature encoder. Edges $\mathcal{E}_i = \{\sigma(u_{i,j}, u_{i,k})\}$, where σ is an edge feature encoder. Like the Interaction Networks (IN) (Battaglia et al., 2016), we propagate the node and edge features spatially to obtain node and edge effects. For convenience, we will describe only graph $\mathcal{G}_i$ in the following formula and omit the index i. Let V_j be the encoded node feature of j, and h_j be the node effect. Similarly, let $\mathcal{E}_{j,k}$ be the encoded edge feature, $h_{j,k}$ be the edge effect. Initially, $h_j = V_j, h_{j,k} = \mathcal{E}_{j,k}$. Then the graph iterates several times to propagate the effect:

$$h_j = \Psi^{\text{node}}(V_j, h_j, \sum_k h_{k,j}) \tag{2}$$

$$h_{j,k} = \Psi^{\text{edge}}(h_j, h_k, h_{j,k}) \tag{3}$$

In the end, we obtain edge $(\mathcal{E}_{i,j}, h_{i,j})$, and compute the probabilistic distribution over the type of the edge (cut or retain). Here we apply the Gumbel-Softmax trick (Jang et al., 2016; Maddison

et al., 2016) to sample the discrete edge type, so the gradients can be back-propagated in end-to-end training. Considering that it is the local communication graph of agent i, only the types of $\mathcal{E}_{i,-i}$ are sampled. If edge $\mathcal{E}_{i,j}$ is retained, agent i will send $G^*_{i,j}$ to j.

Communication Reduction (CR). The message-sender network learns in an end-to-end manner. If no regularization is applied here, the network tends to learn a relatively dense communication connection graph. However, some of these connections are actually redundant. In fact, some receivers choose the same goals with and without these messages. Therefore, we can figure out the necessity of certain communication edges. Formally, we estimate the effect of the received messages to agent i by measuring the KL-divergence between g_i and g_i^-, referred as $\chi = D_{KL}(g_i^- || g_i)$. Note that g_i^- denotes the probability distribution over the goals of agent i when all the messages sent to i are masked. If $\chi < \tau$, we regard that the messages are redundant to agent i. Thus the edges pointing at i will be 'cut'. Otherwise ($\chi > \tau$), we 'retain' all the edges to agent i. Here τ is a constant, regarded as a threshold. Supervised by the generated pseudo labels, the model learns to cut the redundant connections, leading to a more efficient communication network.

3.4 Decision Making

Once the agent receives all the messages, it can decide its own goals of targets based on its observation, inferred goals of others and received messages. Therefore, the actor-critic feature $\eta_i = (\vec{E}_i, \max_k \vec{G}^*_{i,k}, \sum_s \vec{G}^*_{s,k})$. The second term refers to the max inferred probability of a target to be chosen by another agent. The third term refers to the sum of the messages from others, indicating how much certain others infer that agent i should choose the target. The actor decides its goals g_i according to η_i. The centralized critic obtain global feature $(\eta_1, ...\eta_n)$ to compute value. The low-level executor $\pi_i^L(a_i|o_i, g_i)$ takes primitive action to accomplish the sub-goal.

3.5 Training

The model can be divided into ToM net and other parts. While training, the ToM net is supervised by the true observation and goal of others. Other parts are trained by reinforcement learning. We adopt standard A2C (Mnih et al., 2016) as the RL training algorithm, while any MARL method with CTDE framework is also applicable, such as PPO (Schulman et al., 2017; Yu et al., 2021).

Learning ToM Net. We introduce two classification tasks to learn the ToM Net, which is parameterized by θ^{ToM}. First, the ToM net infers the goals $\vec{G}^*_i$ of others. Note that $g^*_{i,j,q}$ indicates the probability of agent j choosing target q, inferred by i. Meanwhile, agent j decides its real goals g_j. Therefore, g_j can be the label of $g^*_{i,j}$. The Goal Inference loss is the binary cross entropy loss of this classification task:

$$L^{GI} = -\frac{1}{N} \sum_i \sum_{j \neq i} \sum_q [g_{j,q} \cdot \log(g^*_{i,j,q}) + (1 - g_{j,q}) \cdot \log(1 - g^*_{i,j,q})] \tag{4}$$

Secondly, the estimated observation representation ϵ is learned in the auxiliary task mentioned before. The agent i infers the relation between the targets and agent j, denoted as $c^*_{i,j}$. The ground truth is the real observation field c_j. $c_{j,q} = 1$ indicates that agent j observes target q or landmark q is closest to agent j. Similar to the previous Goal Inference task, this Observation Estimation learning also adopts binary cross entropy loss:

$$L^{OE} = -\frac{1}{N} \sum_i \sum_{j \neq i} \sum_q [c_{j,q} \cdot \log(c^*_{i,j,q}) + (1 - c_{j,q}) \cdot \log(1 - c^*_{i,j,q})] \tag{5}$$

$$L(\theta^{\text{ToM}}) = L^{GI} + L^{OE} \tag{6}$$

Training Strategy. We find that it is hard for an agent to learn long-term planning from scratch. Therefore, we set the initial episode length L and discount factor γ to a low value, forcing agents to learn short-term planning first. During training, the episode length and discount factor γ increase gradually, leading the agents to estimate the value on a longer horizon.

Furthermore, we freeze the ToM net while the other parts of the model (parameterized by θ^{other}) are updated through RL. The reason is that the ToM net infers the goals of others, and the policy network is continuously updated during RL training. Meanwhile, the output of ToM net is a part of the input to the policy network. If we train them simultaneously, they are likely to influence each other in a nested loop. Therefore, we only collect the ToM inferred data into a batch during RL training. Once the batch is large enough, we stop RL and start ToM training to minimize ToM loss in Eq. 6.

4 EXPERIMENTS

We evaluate ToM2C in two typical target-oriented multi-agent tasks: cooperative navigation (Lowe et al., 2017) and multi-sensor target coverage (Xu et al., 2020). In the cooperative navigation task (CN), n agents need to occupy n landmarks (targets) so as to minimize the distances of all landmarks to their nearest agents. In the multi-sensor multi-target coverage task (MSMTC), n agents need to cooperatively adjust the sensing orientation to maximize the coverage rate of m targets. We compare our method with 4 state-of-the-art MARL methods: TarMAC (Das et al., 2019), I2C (Ding et al., 2020), HiT-MAC (Xu et al., 2020), and MAPPO (Yu et al., 2021). Besides, we report the performance of a heuristic global search policy in MSMTC, as a reference. We further conduct an ablation study to validate the contribution of ToM net and message sender. Finally, we show the good scalability of our model in different populations, comparing with HiT-MAC.

4.1 TASKS AND SETUPS

In the cooperative navigation task (Lowe et al., 2017), n agents try to occupy n landmarks. Agents can observe the relative positions of other landmarks and agents. All agents share a team reward, which is the sum of the negative distance of each landmark to its nearest agent. If two agents collide, the team will get a penalty -1. So the overall team goal is to occupy landmarks one on one and avoid collision. In this task, we set $n = 7$.

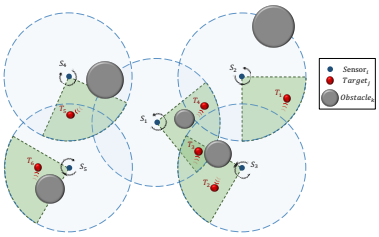


Figure 3: An example of the target coverage environment with obstacles.

The environment of the multi-sensor multi-target coverage task is modified based on the one used in HiT-MAC (Xu et al., 2020). As is shown in Fig.3, each sensor can only see the targets that are within the radius and not blocked by any obstacle. There are 2 types of target: destination-navigation and random walking. The former one moves in the shortest path to reach a previously sampled destination. The latter one moves randomly at each time step. The primitive action for a sensor is to stay or rotate +5/-5 degrees. For our method, the high-level action is the chosen goals g_i. Although the low-level executor can be trained by reinforcement learning (RL) as HiT-MAC, we find a simple rule-based policy can also work well in most cases. Therefore we only train the high-level policy. The reward is the coverage rate of targets. If there is no target covered by sensors, we punish the team with a reward $r = -0.1$. Note that ToM2C agent only selects one landmark as its goal in cooperative navigation, while it can select any number of targets as goals in MSMTC. More details about the environments are in the Appendix. A

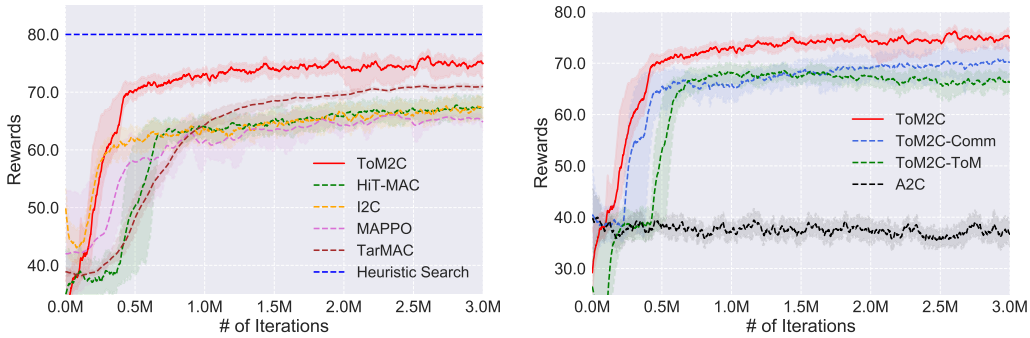
4.2 COMPARE WITH BASELINES

We compare our methods with 4 baselines. TarMAC (Das et al., 2019) is a multi-agent communication method that requires a broadcast channel. I2C (Ding et al., 2020) proposes an individual communication mechanism, which is also achieved by ToM2C. HiT-MAC (Xu et al., 2020) is a hierarchical method that uses a centralized coordinator to organize the agents. MAPPO (Yu et al., 2021) is a variant of PPO which is specialized for multi-agent settings, running without communication. we also implement a heuristic search algorithm as a reference policy. This policy searches in one step for the primitive actions of all the sensors to minimize the sum of minimum angle distance of a target to a sensor. Note that the heuristic search policy exploits the global state to do the global search, while all the other methods are restricted to local observation. Therefore the heuristic search policy can serve as a reference 'upper bound' that evaluates all the MARL baselines.

ToM2C is a hierarchical method, while some of the baselines are not. In MSMTC, we let all of the methods share the low-level rule-based policy adopted in ToM2C. Therefore, these baselines are only used for training the high-level policy, same as ToM2C. In CN, ToM2C and HiT-MAC share the low-level policy and other methods keep non-hierarchical.

Table 1: Quantitative Results in Cooperative Navigation.

	ToM2C	TarMAC	I2C	HiT-MAC	MADDPG	MAPPO
Reward	-0.79 $\pm$ 0.39	-2.14 $\pm$ 0.24	-1.59 $\pm$ 0.40	-0.61 $\pm$ 0.14	-2.75 $\pm$ 0.61	-2.47 $\pm$ 0.21



(a) (b)

Figure 4: The learning curve of our method with baselines and reference policies in the MSMTC scenario. The learning-based methods are all trained in environment with 4 sensors and 5 targets. (a) comparing ours with baselines; (b) comparing ours with its ablations.

Quantitative Results. In CN, as Tab. 1 shows, ToM2C and HiT-MAC are far better than other methods. Here we also add MADDPG as a baseline method, because this environment is early adopted in the original paper of MADDPG (Lowe et al., 2017). The performance of HiT-MAC is slightly better than ToM2C. It is because the hierarchical structures of ToM2C and HiT-MAC are different. For HiT-MAC, there is a centralized coordinator that collects all the local observations and assigns the goals for each agent. On the contrary, ToM2C agents run in a fully decentralized manner. Agents only have access to local observations and decide their own goals. The hierarchy structure is only used for separate goal selections and primitive actions. Due to the centralized manner, HiT-MAC is likely to degrade in complexer scenarios(for example MSMTC), or larger scales. Moreover, HiT-MAC is also more costly in communication(sec. 4.4) and weaker in scalability(sec. 4.5). Therefore, ToM2C is not inferior to HiT-MAC.

In MSMTC, as Fig.4(a) shows, ToM2C achieves the second highest reward (75) in the setting of 4 sensors and 5 targets, only lower than the searching policy (80). The reward performance of I2C, MAPPO and HiT-MAC are all around 66. TarMAC reaches a reward of 71, which is superior to the other three baselines. This could be attributed to the broadcast channel adopted by TarMAC. Since all the methods leverage the hierarchy structure, the superiority of ToM2C comes from the model and training strategies.

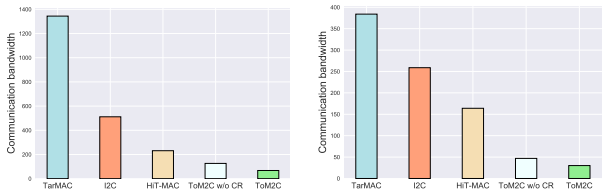
4.3 Ablation Study

We conduct this study to evaluate the contribution of two key components in our model: ToM net and Message sender. The ToM2C-Comm model abandons communication, so the actor makes decisions only based on local observation and inferred goals of others. The ToM2C-ToM abandons ToM net, but keeps the Messages sender. However, as explained before, the local graph node feature is computed based on the ToM net output. To deal with this problem, we use the encoded observation E_j to replace the original node feature $u_{i,j}$. In this way, the n local graphs degrade into one global graph, so the ToM2C-ToM model actually breaks the local communication mechanism. If we remove both the ToM net and Message sender, ToM2C will become pure A2C. We show in Fig.4(b) that if we abandon one of the key components, the performance will drop. Considering that ToM2C-Comm outperforms ToM2C-ToM and ToM net is actually essential for communication, we argue that ToM net mainly contributes to our method.

4.4 Communication Analysis

We compare our method with several candidates in regard to communication expenses. There are 2 metrics here: the number of communication edges and communication bandwidth. The latter metric considers both the count of edges and the length of a single message. TarMAC utilizes a broadcast channel, so there are two communication edges between each pair. The communication in HiT-MAC is between the executors and the coordinator. ToM2C w/o CR refers to the ToM2C model without communication reduction. Apparently, communication band-

width is more significant in real applications, so we place the figure of communication bandwidth in the main text. The statistics of communication edges can be found in Appendix. D. As is shown in Fig.5, the communication bandwidth of ToM2C and ToM2C without CR are much lower than TarMAC, I2C and HiT-MAC. It is because in ToM2C the message is only the inferred goals, while TarMAC, I2C and HiT-MAC have to send the local observation. Therefore, the single message in ToM2C is much simpler than that of TarMAC, I2C and HiT-MAC. As a result, the communication cost of ToM2C is extremely less than existing methods.



(a) (b)

Figure 5: The communication bandwidth of models in (a) Cooperative navigation and (b) MSMTC.

4.5 SCALABILITY

We evaluate the scalability of our method to a different number of sensors and targets in the MSMTC task. Note that the model is only trained in the setting of 4 sensors and 5 targets, so this could be regarded as zero-shot transfer. Since the difficulty of the task changes with the scale of cameras and targets, we make use of the heuristic search policy, whose target coverage rate in each setting can serve as a referential value. We adopt such a metric that divides the coverage rate of the model by the coverage rate of the search policy: $R^{\mathrm{ToM}}_{p,q} = C^{\mathrm{ToM}}_{p,q} / C^{\mathrm{HS}}_{p,q}$, where $C^{\mathrm{ToM}}_{p,q}$ refers to the coverage rate of ToM2C in the setting of p cameras and q targets and $C^{\mathrm{HS}}_{p,q}$ refers to the coverage rate of heuristic search. In this way, we may reduce the fluctuation induced by the change of task difficulty. To better show the advantage of our method, we further test the scalability of HiT-MAC. The experiments are conducted in a total of 81 settings, where cameras and targets both range from 2 to 10. We compute R^{ToM} and R^{HM}(ratio of HiT-MAC and heuristic search) in all the settings and draw the heatmap in Fig. 6. It is shown in the left figure that the ratio R^{ToM} stays near 1, which means that the performance of ToM2C is close to heuristic search in all the settings. Furthermore, if we compare the heatmap of ToM2C and HiT-MAC, it is obvious that ToM2C is more stable than HiT-MAC when transferred to different scales. In this way, we show that ToM2C has a rather strong generalization.

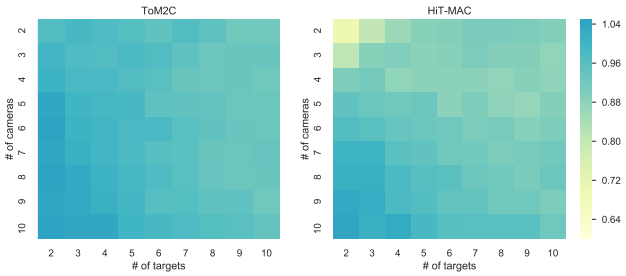


Figure 6: Analyzing the scalability in scenarios with different sizes of cameras and targets. The left heatmap shows R^{ToM}. The right heatmap shows R^{HM}.

5 CONCLUSION

In this work, we study the target-oriented multi-agent cooperation (ToMAC) problem. Inspired by the cognitive study in Theory of Mind (ToM), we propose an effective Target-orient Multi-agent Cooperation and Communication mechanism (ToM2C) for ToMAC. For each agent, ToM2C is composed of an observation encoder, ToM net, message sender, and decision-maker. The ToM net is designed for estimating the observation and inferring the goals (intentions) of others. It is also deeply used by the message sender and decision-making. Besides, a communication reduction method is proposed to further improve the efficiency of the communication. Empirical results demonstrated that our method can deal with challenging scenes and outperform the state-of-the-art MARL methods.

Although impressive improvements have been achieved, there is still a number of limitations of this work leaving for addressed by future works. 1) The model is only evaluated in two simulated scenarios. But the environment we used contains most features that other applications, e.g. partial observation, team reward structure. And each component in the model is general. So we are confident to extend ToM2C to more realistic applications in the future. 2) Besides, the communication reduction method can also be further optimized, as the pseudo labels we generated for communication reduction are noisy in some cases.

REPRODUCIBILITY STATEMENT

The code of ToM2C has been zipped into the supplementary material. The details of the task environments can be found in Appendix. A. The hyper-parameters used in ToM2C are listed in Tab. 2.

REFERENCES

Peter Battaglia, Razvan Pascanu, Matthew Lai, Danilo Jimenez Rezende, and Koray kavukcuoglu. Interaction networks for learning about objects, relations and physics. In *Proceedings of the 30th International Conference on Neural Information Processing Systems*, pp. 4509–4517, 2016.

Daniel S Bernstein, Robert Givan, Neil Immerman, and Shlomo Zilberstein. The complexity of decentralized control of markov decision processes. *Mathematics of operations research*, 27(4): 819–840, 2002.

Abhishek Das, Théophile Gervet, Joshua Romoff, Dhruv Batra, Devi Parikh, Mike Rabbat, and Joelle Pineau. Tarmac: Targeted multi-agent communication. In *International Conference on Machine Learning*, pp. 1538–1546. PMLR, 2019.

gang Ding, Tiejun Huang, and Zongqing Lu. Learning individually inferred communication for multi-agent cooperation. In *Advances in Neural Information Processing Systems*, volume 33, pp. 22069–22079, 2020.

Evren Etel and Virginia Slaughter. Theory of mind and peer cooperation in two play contexts. *Journal of Applied Developmental Psychology*, 60:87–95, 2019.

Jakob N Foerster, Gregory Farquhar, Triantafyllos Afouras, Nantas Nardelli, and Shimon Whiteson. Counterfactual multi-agent policy gradients. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018.

Aditya Grover, Maruan Al-Shedivat, Jayesh Gupta, Yuri Burda, and Harrison Edwards. Learning policy representations in multiagent systems. In *International Conference on Machine Learning*, pp. 1802–1811. PMLR, 2018.

He He, Jordan Boyd-Graber, Kevin Kwok, and Hal Daumé III. Opponent modeling in deep reinforcement learning. In *International Conference on Machine Learning*, pp. 1804–1813. PMLR, 2016.

Shariq Iqbal and Fei Sha. Actor-attention-critic for multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 2961–2970. PMLR, 2019.

Eric Jang, Shixiang Gu, and Ben Poole. Categorical reparameterization with gumbel-softmax. *arXiv preprint arXiv:1611.01144*, 2016.

Jiechuan Jiang, Chen Dun, Tiejun Huang, and Zongqing Lu. Graph convolutional reinforcement learning. In *International Conference on Learning Representations*, 2019.

Yunzhu Li, Antonio Torralba, Anima Anandkumar, Dieter Fox, and Animesh Garg. Causal discovery in physical systems from videos. *Advances in Neural Information Processing Systems*, 33, 2020.

Terence X Lim, Sidney Tio, and Desmond C Ong. Improving multi-agent cooperation using theory of mind. *arXiv preprint arXiv:2007.15703*, 2020.

Ryan Lowe, Yi Wu, Aviv Tamar, Jean Harb, OpenAI Pieter Abbeel, and Igor Mordatch. Multi-agent actor-critic for mixed cooperative-competitive environments. In *Advances in Neural Information Processing Systems*, pp. 6379–6390, 2017.

Chris J Maddison, Andriy Mnih, and Yee Whye Teh. The concrete distribution: A continuous relaxation of discrete random variables. *arXiv preprint arXiv:1611.00712*, 2016.

Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International Conference on Machine Learning*, pp. 1928–1937, 2016.

David Premack and Guy Woodruff. Does the chimpanzee have a theory of mind? *Behavioral and brain sciences*, 1(4):515–526, 1978.

Neil Rabinowitz, Frank Perbet, Francis Song, Chiyuan Zhang, SM Ali Eslami, and Matthew Botvinick. Machine theory of mind. In *International conference on machine learning*, pp. 4218–4227. PMLR, 2018.

Roberta Raileanu, Emily Denton, Arthur Szlam, and Rob Fergus. Modeling others using oneself in multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 4257–4266. PMLR, 2018.

Tabish Rashid, Mikayel Samvelyan, Christian Schroeder, Gregory Farquhar, Jakob Foerster, and Shimon Whiteson. Qmix: Monotonic value function factorisation for deep multi-agent reinforcement learning. In *International Conference on Machine Learning*, pp. 4295–4304. PMLR, 2018.

Alan G Sanfey, Claudia Civai, and Peter Vavra. Predicting the other in cooperative interactions. *Trends in cognitive sciences*, 19(7):364–365, 2015.

John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017.

Itai Sher, Melissa Koenig, and Aldo Rustichini. Children's strategic theory of mind. *Proceedings of the National Academy of Sciences*, 111(37):13307–13312, 2014.

Tianmin Shu and Yuandong Tian. M^3rl: Mind-aware multi-agent management reinforcement learnings. In *International conference on learning representations*, 2019.

Michael Shum, Max Kleiman-Weiner, Michael L Littman, and Joshua B Tenenbaum. Theory of minds: Understanding behavior in groups through inverse planning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, pp. 6163–6170, 2019.

Amanpreet Singh, Tushar Jain, and Sainbayar Sukhbaatar. Individualized controlled continuous communication model for multiagent cooperative and competitive tasks. In *International conference on learning representations*, 2019.

Sainbayar Sukhbaatar, arthur szlam, and Rob Fergus. Learning multiagent communication with backpropagation. 29, 2016.

Peter Sunehag, Guy Lever, Audrunas Gruslys, Wojciech Marian Czarnecki, Vinícius Flores Zambaldi, Max Jaderberg, Marc Lanctot, Nicolas Sonnerat, Joel Z Leibo, Karl Tuyls, et al. Value-decomposition networks for cooperative multi-agent learning based on team reward. In *AAMAS*, pp. 2085–2087, 2018.

Michael Tomasello. *A natural history of human thinking*. Harvard University Press, 2014.

Socially Interactive Agents Track, Jan Pöppel, and Stefan Kopp. Satisficing models of bayesian theory of mind for explaining behavior of differently uncertain agents. In *Proceedings of the 17th International Conference on Autonomous Agents and Multiagent Systems, Stockholm, Sweden*, pp. 10–15, 2018.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *arXiv preprint arXiv:1706.03762*, 2017.

Sarah A Wu, Rose E Wang, James A Evans, Joshua B Tenenbaum, David C Parkes, and Max Kleiman-Weiner. Too many cooks: Bayesian inference for coordinating multi-agent collaboration. *Topics in Cognitive Science*, 13(2):414–432, 2021.

Jing Xu, Fangwei Zhong, and Yizhou Wang. Learning multi-agent coordination for enhancing target coverage in directional sensor networks. In *Advances in Neural Information Processing Systems*, volume 33, pp. 10053–10064, 2020.

Chao Yu, Akash Velu, Eugene Vinitsky, Yu Wang, Alexandre Bayen, and Yi Wu. The surprising effectiveness of mappo in cooperative, multi-agent games. *arXiv preprint arXiv:2103.01955*, 2021.

A DETAILS OF ENVIRONMENT

A.1 MULTI-SENSOR TARGET COVERAGE

The multi-sensor multi-target tracking environment is developed based on the previous version in HiT-MAC(Xu et al., 2020), and it inherits most of the characters. It is a 2D environment that simulates the real target coverage problem in directional sensor networks. Each sensor can only see the targets that are within the radius and not blocked by any obstacle. There 2 types of target: destination-navigation and random walking. The former one moves in the shortest path to reach a previously sampled destination. The latter one moves randomly at each time step. At the beginning of each episode, the location of sensors, targets and obstacles are randomly sampled. Besides, the type of the targets are also sampled according to a pre-defined probability. The length of an episode is 100 steps.

Observation Space. At each time step, the local observation o_i is a set of agent-target pairs: $(o_{i,1}, ...o_{i,m})$. If target q is visible to agent i, then $o_{i,q} = (i, q, d_{i,q}, \alpha_{i,q})$, where $d_{i,q}$ is the distance and $\alpha_{i,q}$ is the relative angle. If target q is not visible to i, then $o_{i,q} = (0, 0, 0, 0)$. Therefore, $o_i \in \mathbb{R}_{m\times 4}$.

Action Space. The primitive action for a sensor is to stay or rotate +5/-5 degrees. For our method, the high-level action is the chosen goals g_i, which is a binary vector of length m. $g_{i,q} = 1$ means the agent chooses target q as one of its goals. $g_{i,q} = 0$ means not. Although the low-level executor can be trained by reinforcement learning (RL) as HiT-MAC, we find a simple rule-based policy can also work well in most cases. Therefore we only train the high-level policy.

Reward. Reward is the coverage rate of targets: $r = \frac{1}{m}\sum_q I_q$, where $I_q = 1$ if q is covered by any sensor. If there is no target covered by sensors, we punish the team with a reward $r = -0.1$.

Compared with the version in HiT-MAC, we add some new features to make it more complex and realistic.

First, HiT-MAC assumes that all the agents can see all the targets in the environment, which is unreasonable for real applications. Therefore, we change this setting into a Dec-POMDP, in which an agent can only obtain the information in its local observation. For those targets that are out of view, the corresponding observation will be a zero vector.

Secondly, we add another kind of objects, obstacles, into the environment. The obstacles are all circles in this 2D plain simulator, varying in the radius. The targets within the observation radius will still be invisible if it is shadowed by an obstacle.

Finally, in the original environment all the targets move in a goal-oriented manner. The targets sample their destinations at the beginning of an episode and navigate themselves to the destinations. Nevertheless, not all targets in real world follow the same action pattern. Therefore, we fill the environment with a mixed-type population of targets. The target can either be goal-oriented or random-walking. When the target is random-walking, it will randomly sample a primitive action to take at each step. In this way, the movement of targets is harder to predict, raising the difficulty of the planning.

A.2 COOPERATIVE NAVIGATION

The environment is similar to one used in MADDPG (Lowe et al., 2017). The length of each episode is 100 steps. For hierarchical methods, the high-level episode length is set to 10, and each high-level step consists of 10 low-level steps. Therefore, the primitive action series of different methods are of the same length. Similar to the multi-sensor target coverage task, ToM2C and HiT-MAC again make use of a rule-based low-level policy.

B TOM2C

Network Architecture and Hyper-parameters for ToM2C. The observation encoder consists of 2-layer multilayer perceptron (MLP) and an attention module: $\mathtt{att}_1$. The ToM net consists of a Gated Recurrent Unit (GRU) and 2-layer MLP. The message sender is a Graph Neural Network (GNN) and

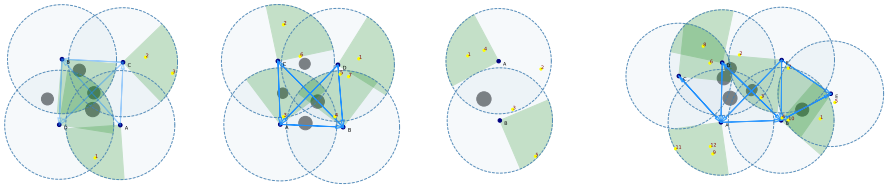


Figure 7: Snapshots of the multi-sensor multi-target tracking environments with different scales. From the upper left figure, in the clockwise direction, they are 4 vs 3, 4 vs 7, 2 vs 5, and 6 vs 12, respectively.

the actor consists of one fully connected layer. The critic consists of an attention module att_2 that can handle different numbers of agents. As mentioned before, the basic RL training algorithm is A2C, and the hyper-parameters are detailed in Tab. 2.

Table 2: Hyper-parameters for ToM2C

Hyper-parameters	#	Description
GRU hidden units	32	the # of hidden units for GRU
att_1 hidden units	64	the # of hidden units for att_1
att_2 hidden units	192	the # of hidden units for att_1
max steps	3M	maximum environment steps sampled in workers
episode length	100	maximum time steps per episode
discount factor	0.9	discount factor for rewards
entropy weight	0.005	parameter for entropy regularization
learning rate	1e-3	learning rate for all networks
workers	6	the # of workers for sampling
update frequency	20	the network updates every # steps in A2C
ToM Frozen	5	the ToM net is frozen for every # times of RL training
gamma rate	0.002	the increasing rate of discounting factor γ

Training Strategy. There are two training strategies adopted to accelerate training and stabilize the result. As mentioned in Sec.3.5, one is to increase episode length L and γ factor gradually during training, the other one is to split the optimization of the ToM and RL model.

In this paper, we propose this curriculum learning strategy that gradually increases episode length L and discounting factor γ. Usually, the discounting factor γ is set larger than 0.9 to encourage long-term planning in RL algorithms. Furthermore, the length of an episode is usually determined by the environment. We notice that if using the default hyper-parameters, the agents are sample inefficient and unstable while learning. In our experiments, we set $L = 20$ and $\gamma = 0.1$ initially. After 2000 episodes of warm-up, the γ factor will be updated according to a pre-set rate β. Each time the network is optimized through reinforcement learning, $\gamma = \gamma * (1 + \beta)$, where $\beta = 0.002$ in this paper. Simultaneously, the episode length L is updated with γ. In fact, $L = \lfloor \frac{\gamma+0.1}{0.2} \rfloor \times 20$. In the end, $\gamma = 0.9$ and $L = 100$. By doing so, the agents learn short-term planning first, and then adapt to a longer horizon. We find in experiments that such strategy accelerates the training process, leading to a faster convergence and a better performance.

Furthermore, we separate the optimizations of the ToM and RL model in implementation. Before the training process starts, the parameters of our model are split into two parts: θ^{ToM} and θ^{other}. Each part is optimized individually by a different optimizer. Since we adopt A2C as the base RL training algorithm, we collect trajectories data from different worker processes and send them to the training process when all the running episodes end. After that, θ^{other} is optimized with regard to the A2C loss. Meanwhile, the trajectories data for ToM training are saved instead of being used for training ToM net immediately. In this way, the ToM net is 'frozen'. θ^{ToM} will be optimized with regard to ToM loss after θ^{other} has been optimized for T_F times. Here we choose $T_F = 5$. Just like

the discussion before, the separation of ToM and RL training avoids the nested loop of influence among the ToM net and the policy network.

The environment and model are implemented in Python. The model is built on PyTorch and is trained on a machine with 7 Nvidia GPUs (Titan Xp) and 72 Intel CPU Cores.

C BASELINES

Heuristic Search Method. To evaluate the performance of our ToM2C model, we choose to implement a heuristic search policy to serve as a reference. This search policy is applied to select low-level sensor action(Stay, Turn Left/Right). At each step, the policy searches all the 3^n possibilities of combination of actions, where n is the number of sensors. The goal is to find the action combination that minimizes the angle distance of targets to sensors. Specifically, we denote the angle distance of target j to sensor i as α_{ij}. Then the objective is to minimize $\sum_{j=1}^{m} \min_i\{\alpha_{ij}\}$. It is obvious that such searching policy only considers one step, thus not the optimal policy. However, we show that this naive heuristic search can reach 80% target coverage. As a result, it can serve as a reference 'upper bound' that evaluates all the MARL baselines.

MARL Baselines. The code of HiT-MAC and I2C are from their official repositories. We follow the default hyper-parameters in their code, except that we change the learning rate, discounting factor γ and episode length to be the same as ToM2C. TarMAC is implemented on our own because no official code is released. Moreover, HiT-MAC is a hierarchical method, so we simply train the high-level coordinator and use the same rule-based low-level policy utilized in ToM2C. On the other hand, I2C is not a hierarchical method and it is not target-oriented. As a result, we concatenate all the target information into one vector as the observation for I2C. The action space is modified as the set of choice of all the targets, so the space size is 2^m, where m is the number of targets. In this way, the output action of I2C agent is the selection of goal targets, same as HiT-MAC and ToM2C. Once the goal target is selected, the primitive actions will be chosen by the rule-based policy.

D QUANTITATIVE RESULTS

For MSMTC task, We list the **coverage rate** achieved by different methods in Tab. 3. The mean and standard deviation are computed based on the data collected in 1000 episodes. The performance in cooperative navigation is listed in Tab. 1.

Table 3: Coverage Rate in 4 sensors vs 5 targets scenario

Methods	Coverage Rate(%)↑
A2C	38.44 ± 0.54
HiT-MAC	61.48 ± 1.45
I2C	66.29 ± 1.40
MAPPO	66.87 ± 0.69
ToM2C-ToM	67.66 ± 0.63
TarMAC	70.56 ± 0.81
ToM2C-Comm	71.61 ± 0.31
ToM2C(Ours)	$\mathbf{75.38} \pm \mathbf{0.57}$

Apart from the coverage rate, we analyze the communication efficiency of different methods. There are 2 metrics introduced in this paper. Communication edges refer to the count of directed communication pairs. One edge from i to j means that agent i sends a message to agent j. Communication bandwidth refers to the total volume of messages. As we mentioned in the experiment section, it is the volume of messages that has a decisive effect on the cost of communication. Since the messages are all float-type vectors, we use the length of a message instead of the number of bits to represent the volume of a single message. For I2C, the message from agent i is the local observation o_i, containing the information of all the targets. For HiT-MAC, communication happens between the executors and the coordinator. The executors send their local observation to the coordinator, and the coordinator

Table 4: Communication Statistics of MSMTC

Methods	Communication Edges	Communication Bandwidth↓
TarMAC	12.00 ± 0.00	384.00 ± 0.00
I2C	7.19 ± 0.13	258.84 ± 4.16
HiT-MAC	8.00 ± 0.00	164.00 ± 0.00
ToM2C w/o CR	9.39 ± 0.19	46.93 ± 0.97
ToM2C(Ours)	$\mathbf{6.03} \pm \mathbf{0.20}$	$\mathbf{30.15} \pm \mathbf{1.02}$

Table 5: Communication Statistics of CN

Methods	Communication Edges	Communication Bandwidth↓
TarMAC	42.00 ± 0.00	1344.00 ± 0.00
I2C	14.21 ± 1.65	511.41 ± 59.44
HiT-MAC	14.00 ± 0.00	231.00 ± 0.00
ToM2C w/o CR	42.00 ± 0.00	126.00 ± 0.00
ToM2C(Ours)	$\mathbf{22.48} \pm \mathbf{0.91}$	$\mathbf{67.44} \pm \mathbf{2.74}$

returns the goal assignment. For ToM2C w/o CR and ToM2C, the message is simply the inferred goals of the receiver. ToM2C w/o CR means that the trained ToM2C model is not further optimized to reduce communication.

The experiments are conducted in the 4-sensors-and-5-targets scenario and 7v7 cooperative navigation. As shown in Tab. 4 and Tab. 5, our method achieves the lowest communication cost.

E DEMO SEQUENCE

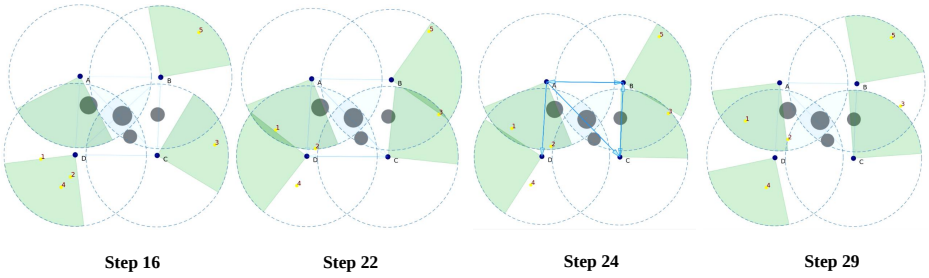


Figure 8: An exemplar sequence in 4 sensors and 5 targets MSMTC environment. The gray circle indicates the obstacle. The arrows are rendered as solid only when the communication happens, and transparent at other times.

To better understand the learned behavior, we render the target coverage environment and show a typical demo sequence in Fig. 8. It consists of 4 consecutive keyframes in one episode. The arrows between sensors indicate communication connections. Note that communication only happens every 10 steps. In step 16, sensor D can track target 1, 2 and 4. However when it comes to step 22, sensor D can no longer track all the three targets, so it starts to hesitate about which targets to track. Then in step 24, A sends a message to D, and D inferred that A would track target 1 and 2. Therefore, it re-plans its own goal to be target 4. In the end, we can see that sensor D really abandons target 1 and 2, and focuses on target 4.