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 the multi-sensor target coverage problem, a typical target-oriented multi-agent task. The experiments show that the proposed model not only outperforms the state-of-the-art methods on target coverage rate 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; Eiel & 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).

Motivated by this, machine learning researchers have spent efforts on developing the machine ToM (Rabinowitz et al., 2018) or modeling opponents (He et al., 2016) for multi-agent learning (Raileanu et al., 2018; Grover et al., 2018; Lim et al., 2020). But most of the existing computing models are only used in toy environments, where there are only a few agents (two or three) performing simple tasks. It is still challenging to implement such a thinking mechanism for social agents, especially in cases of a number of agents. It is because the mental state of one agent will be impacted by others, leading to drops in ToM accuracy and efficiency.

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

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.

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 according to local observation filtered by the inferred goals of others. The message is rather simple and comprehensible, which is only 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 to the expected.

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 systematically 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 (Xu et al., 2020). 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 ratio among the state-of-the-art MARL methods, e.g., I2C (Ding et al., 2020) and HiT-MAC (Xu et al., 2020). Moreover, we also show good scalability of ToM2C in different populations of sensors and targets. We further conduct an ablation study to evaluate the contribution of each key component of our model.

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 show that our model not only outperforms the state-of-the-art MARL methods in coverage rate 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 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 behaviours, 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 behaviours or characteristics of a single agent. Besides, Shum et al. (Shum et al., 2019) studies how to apply Bayesian inference to understand the behaviours of a group and predict the group structure. Track et al. (Track et al., 2018) introduces the concept of Satisficing Theory of Mind, which means the sufficing and satisfying model of others. None of these works looks into the problem of multi-agent cooperation. Lim et al. (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. On the other hand, opponent modeling (He et al., 2016; Raileanu et al., 2018; Grover et al., 2018) is another kind of methods 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 net, and actor-critic net. 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 $\epsilon_j$ of each other agents according to their poses. $\epsilon_j$ can be used for inferring the currently visible targets of agent $j$, which is an auxiliary task that will be discussed later. Based on $\epsilon_j$ 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 net. The node feature of agent $j$ is the concatenation of $\epsilon_j$ 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, $G^*_i,j$, $E_i$ and received messages is concatenated as $\eta_i$ for planner(ctor) and critic. Planner $\pi_i^H(g_i|o_i)$ is the high level policy that chooses the goals $g_i$, which guides the low-level executor $\pi_i^{\pi}(a_i|o_i, g_i)$ 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). $m$ is the number of targets. The input is the local observation $\tilde{o}_i \in \mathbb{R}^{m \times d_{obs}}$. The observation is first transformed to key $K_i$, query $Q_i$ and value $V_i$ through 3 different neural networks. Then the output $E_i = \text{softmax}(Q_i K_i^T \sqrt{d_k}) \odot V_i$, where $d_k$ is the dimension of one key, so $\tilde{E}_i \in \mathbb{R}^{m \times d_{att}}$. $\tilde{o}_{i,q}$ and $\tilde{E}_{i,q}$ 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. The 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 $\epsilon_j$, with the pose $\phi_j$. Note that $\epsilon_j$ is only a representation of the observation. To better learn this representation, we introduce an auxiliary task here. Agent $i$ needs to infer which targets are in the observation field of agent $j$, based on this representation $\epsilon_j$ and local observation $\tilde{E}_i$. 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: $G^*_i,j,q = GI(\tilde{E}_{i,q}, \epsilon_j)$. $G^*_i,j,q$ stands for the probability of agent $j$ choosing target $q$, inferred by $i$. Since there are a total of $n$ agents and $m$ target in the environment, $G^*_i \in \mathbb{R}^{(n-1)\times m}$.

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 con-
nection, 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 the 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. $\delta$ is a probability threshold, if $G^*_{i,j} > \delta$, then agent $i$ considers it as the goal that will be chosen by agent $j$.

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

Then we concatenate the filtered feature $E'_{i,j}$ with the estimated observation representation $\epsilon_j$, 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 $\epsilon_i$ 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 $G = (G_1, G_2, ..., G_n)$. $G_i = (V_i, E_i)$ is the local graph for agent $i$ to compute the communication connection from agent $i$. The vertice $V_i = \{f(u_{i,j})\}$, where $f$ is a node feature encoder. Edges $E_i = \{\sigma(u_{i,j}, u_{i,k})\}$, where $\sigma$ 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 $G_i$ 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 $E_{j,k}$ be the encoded edge feature, $h_{j,k}$ be the edge effect. Initially, $h_j = V_j$, $h_{j,k} = E_{j,k}$. Then the graph iterates several times to propagate the effect:

\[
h_j = \Psi^{node}(V_j, h_j, \sum_k h_{k,j})
\]

\[
h_{j,k} = \Psi^{edge}(h_j, h_k, h_{j,k})
\]

In the end, we obtain edge $(E_{i,j}, h_{i,j})$, 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 $E_{i,k}$ are sampled. If edge $E_{i,j}$ 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 $\tau$ 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 $\eta_i = (E_i, \max_k G^*_{i,k}, \sum_k G^*_{i,k})$. 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 $\eta_i$. The centralized critic obtain global feature $(\eta_1, ..., \eta_n)$ to compute value. The low-level executor $\pi^L(a_i|o_i, g_i)$ takes primitive action to accomplish the sub-goal.

### 3.5. Training

The model can be divided into ToM net and other parts. ToM net is trained in supervised learning with the true state 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 $\theta^{ToM}$. First, the ToM net infers the goals $G^*_{i,j}$ 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:

\[
L^{GI} = -\frac{1}{N} \sum_i \sum_j \sum_q (g_{j,q} \cdot \log(g_{i,j,q}^*) + (1 - g_{j,q}) \cdot \log((1 - g_{i,j,q}^*))
\]

Secondly, the estimated observation representation \( \epsilon \) is trained in the auxiliary task mentioned before. The agent \( i \) infers which targets are in the observation field of \( j \), 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 \( q \). Similar to the previous Goal Inference task, this Observation Estimation learning also adopts binary cross entropy loss:

\[
L^{OE} = -\frac{1}{N} \sum_i \sum_j \sum_q (c_{j,q} \cdot \log(c_{i,j,q}^*) + (1 - c_{j,q}) \cdot \log((1 - c_{i,j,q}^*))
\]

\[
L(\theta^{ToM}) = L^{GI} + L^{OE}
\]

**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 \( \gamma \) to a low value, forcing agents to learn short-term planning first. During training, the episode length and discount factor \( \gamma \) 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 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 the challenging multi-sensor target coverage problem. Sensors need to cooperate with others to reach a maximum target coverage rate. We compare our method with 3 state-of-the-art MARL methods: I2C (Ding et al., 2020), HiT-MAC (Xu et al., 2020), A2C (Mnih et al., 2016), and a reference heuristic search policy. We also conduct an ablation study to validate the contribution of ToM net and Message Sender. Finally, we show that our model can generalize to different sizes of agents and targets.

**4.1. Environment**

The environment is modified based on the one used in HiT-MAC (Xu et al., 2020), and it inherits most of the characters. As is shown in Fig.3, 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 are 2 types of target: destination navigation and random walking. The former one moves along 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 types of targets are also sampled according to a pre-defined probability.

**Observation Space.** At each time step, the local observation \( o_i \) is a set of agent-target pairs: \( \{o_{i,1}, \ldots, o_{i,m}\} \). 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 of 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 as in (Xu et al., 2020), we find that a simple rule-based policy can also work well in most cases. Therefore we only train the high-level policy. In this way, other methods without a hierarchical structure are comparable with our method.

**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 \( r = -0.1 \).

**4.2. Baselines**

We compare our methods with 4 baselines. HiT-MAC (Xu et al., 2020) is a hierarchical method that uses a coordinator.
to enhance cooperation. I2C (Ding et al., 2020) proposes an individual communication mechanism, which is also achieved by ToM2C. A2C (Mnih et al., 2016) is a standard reinforcement learning algorithm. Here we employ A2C to train a single agent that selects the goals for all the sensors. Finally, we 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.

4.3. Results

As fig. 4 shows, ToM2C achieves the second highest reward (75) in the setting of 4 sensors and 5 targets, which is only lower than the searching policy (80). The vanilla A2C shows a similar performance to random policy, indicating that the task is not trivial. The reward performance of HiT-MAC is around 62, lower than the result presented in the original paper. This could be attributed to the addition of obstacles. I2C reaches a fair reward of 66, but we will show that such performance is still lower than our ablation models.

Ablation Study. We conduct this study to evaluate the 2 key components of 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. We show in fig.5 that if we abandon one of the key components, the performance will drop. Specifically, ToM2C-Comm reaches 72, and ToM2C-ToM reaches 68, both higher than I2C. 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.

Communication Analysis. We compare our method with several candidates in regard to communication expense. 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. There are 5 candidates here. FC refers to fully connected communication in ToM2C. ToM2C w/o CR refers to the ToM2C model without communication reduction. The communication in HiT-MAC is between the executors and the coordinator. As is shown in fig.6, ToM2C performs the least communication in regard to edge count, but this
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5. Conclusion and Discussion

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-oriented 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 handle 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 left to be addressed by future works. 1) The model is only evaluated in a simulated scenario. However, the environment we used contains most features that many other applications have, e.g. partial observation, team reward structure. Since each component in the model is general, we are confident to extend ToM2C in other application scenarios, e.g. cooperative searching 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.

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Appendix

A. Details of Environment

We conduct the experiments in a multi-sensor multi-target tracking environment. This environment is developed based on the previous version in HiT-MAC (Xu et al., 2020). Differently, 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.

B. ToM2C

Network Architecture and Hyper-parameters for ToM2C. The observation encoder consists of 2-layer multilayer perceptron (MLP) and an attention module: $\text{att}_1$. The ToM net consists of a Gated Recurrent Unit (GRU) and 2-layer MLP. The message sender is a Graph Neural Network (GNN) and the actor consists of one fully connected layer. The critic consists of an attention module $\text{att}_2$ 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. 1.

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 $\gamma$ 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 discount factor $\gamma$. Usually, the discounting factor $\gamma$ 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 $\gamma$ factor will be updated according to a pre-set rate $\beta$. Each time the network is optimized through reinforcement learning, $\gamma = \gamma \ast (1 + \beta)$, where $\beta = 0.002$ in this paper. Simultaneously, the episode length $L$ is updated with $\gamma$. In fact, $L = \left\lfloor \frac{\gamma_{t} + 0.1}{0.2} \right\rfloor \times 20$. 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: $\theta^{\text{ToM}}$ and $\theta^{\text{other}}$. 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, $\theta^{\text{other}}$ is optimized
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Table 1. Hyper-parameters for ToM2C

| Hyper-parameters       | #   | Description                                                                 |
|------------------------|-----|-----------------------------------------------------------------------------|
| GRU hidden units       | 32  | the # of hidden units for GRU                                              |
| att\textsubscript{1} hidden units | 64  | the # of hidden units for att\textsubscript{1}                              |
| att\textsubscript{2} hidden units | 192 | the # of hidden units for att\textsubscript{2}                              |
| 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                                 |

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\textsubscript{ToM} will be optimized with regard to ToM loss after θ\textsubscript{other} has been optimized for T\textsubscript{F} times. Here, we choose T\textsubscript{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\textsuperscript{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\textsubscript{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. 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\textsuperscript{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

We list the coverage rate achieved by different methods in Tab. 2. The mean and standard deviation are computed based on the data collected in 1000 episodes.

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

Table 2. 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       |
| ToM2C-ToM    | 67.66± 0.63       |
| ToM2C-Comm   | 71.61± 0.31       |
| ToM2C(Ours)  | 75.38± 0.57       |

Table 3. Communication Statistics

| Methods     | Communication Edges | Communication Bandwidth↓ |
|-------------|---------------------|--------------------------|
| I2C         | 7.16                | 257.76                   |
| HiT-MAC     | 8.0                 | 164                      |
| FC          | 12.0                | 60                       |
| ToM2C w/o CR| 9.36                | 46.81                    |
| ToM2C(Ours) | 6.02                | 30.08                    |
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 explained 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 returns the goal assignment. For fully connected communication (FC), 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 experiment is conducted in the 4-sensors-and-5-targets scenario. As shown in Tab. 3, our method achieves the lowest communication cost both in communication edges and bandwidth. Moreover, even FC beats I2C and HiT-MAC in communication bandwidth. It is because FC only sends the inferred goals, which is much simpler than the raw observation.

E. Demo Sequence

To better understand the learned behavior, we render the environment and show a typical demo sequence in Fig. 11. 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.