A Game-theoretic Utility Network for Cooperative Multi-Agent Decisions in Adversarial Environments

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Abstract
Underlying relationships among multi-agent systems (MAS) in hazardous scenarios can be represented as Game-theoretic models. We measure the performance of MAS achieving tasks from the perspective of balancing success probability and system costs. This paper proposes a new network-based model called Game-theoretic Utility Tree (GUT), which decomposes high-level strategies into executable low-level actions for cooperative MAS decisions. This is combined with a new payoff measure based on agent needs for real-time strategy games. We present an Explore game domain to evaluate GUT against the state-of-the-art QMIX decision-making method. Conclusive results on extensive numerical simulations indicate that GUT can organize more complex relationships among MAS cooperation, helping the group achieve challenging tasks with lower costs and higher winning rate.

1 Introduction
Natural systems have been the key inspirations in the design, study, and analysis of Multi-Agent Systems (MAS) [Wooldridge, 2009]. Distributed Intelligence refers to systems of entities working together to reason, plan, solve problems, think abstractly, comprehend ideas and language, and learn [Parker, 2007]. Especially for cooperative MAS, the individual is aware of other group members, and actively shares and integrates its needs, goals, actions, plans, and strategies to achieve a common goal and benefit the entire group. It can maximize global system utility and guarantee sustainable development for each group member [Shen et al., 2004].

Systems with a wide variety of agent heterogeneity and communication abilities can be studied, and collaborative and adversarial issues also can be combined in a real-time situation [Stone and Veloso, 2000]. Considering working in adversarial environments, opponents can prevent MAS from achieving global and local tasks, even impair individual or system necessary capabilities or normal functions [Jun and D'Andrea, 2003]. Combining multi-agent cooperative decision-making and robotics disciplines, researchers developed the Adversarial Robotics focusing on autonomous agents operating in adversarial environments. [Agmon et al., 2011; Yehoshua and Agmon, 2015]. From the robot’s1 needs [Yang and Parasuraman, 2020] and motivations perspective, we can classify an Adversary into two general categories: Intentional (such as enemy or intelligent opponent agent, which consciously and actively impairs the MAS needs and capabilities) and Unintentional (like obstacles and weather, which unaware and passively threaten MAS abilities) adversary.

MAS research domains focus on solving path planning problems for avoiding static or dynamical obstacles [Agmon et al., 2011] and formation control [Shapira and Agmon, 2015; Yehoshua and Agmon, 2015] from the unintentional adversary perspective. For intentional adversaries, the "pursuit domain" [Benda et al., 1986; Cheng, 2003] primarily deals with how to guide one or a group of pursuers to catch one or a group of moving evaders [Scott III, 2017; Makkapati and Tsiotras, 2019]. Foundations for normal-form team games and extensive-form adversarial team games are provided in [von Stengel and Koller, 1997] and [Celli and Gatti, 2018], respectively. Nevertheless, it is more realistic and practical for MAS to organize more complex relationships and behaviors, achieving given tasks with higher success probability and lower costs in adversarial environments.

Contributions This paper proposes a new hierarchical network model called Game-theoretic Utility Tree (GUT) to achieve MAS cooperative decision-making in adversarial environments. GUT consists of Game-theoretic Utility Computation Units (Fig. 2) distributed in multiple levels by decomposing strategies, thereby significantly lowering the game-theoretic operations in strategy space dimension. It combines the core principles of Bayesian Networks [Koller and

1Here, we use the terms agent and robot interchangeably.
Friedman, 2009], Game Theory [Myerson, 2013], and Utility Theory [Fishburn, 1970; Kochenderfer, 2015]. Further, we propose a novel way of calculating the payoff (utility) values through the agent needs expectations, which is also organized hierarchically similar to human needs pyramid. We also present a game of Explorers vs. Aliens (referred as “Explore domain” - Fig. 1) to evaluate the MAS performance from the perspective of balancing the success probability of achieving tasks and system costs by organizing involved individuals’ relationships and suitable groups’ strategies in adversarial environments.

We demonstrate the effectiveness of GUT against the state-of-the-art cooperative decision-making algorithm QMIX in extensive realistic simulations of the Explore Domain. The results indicated that GUT could organize more complex relationships among MAS cooperation. It helps the group achieving challenging tasks with lower costs and higher winning probability. The proposed approach can be applied to other Real-Time Strategy (RTS) games, which involve agents decomposing the high-level strategies into primitive actions or group atomic operations [Yang and Parasuraman, 2020], which means that every finite game has a normal form.

Through the above analysis, we adopt Utility Theory to define the agent’s fourth level needs – Teaming Needs (Eq. (4)). It can be regarded as a kind of motivation or requirements for cooperation achieving specific goals or tasks to satisfy the individual or group’s certain Expected Utilities. According to Robot Needs Hierarchy, we define the adversary as follows:

**Definition 1 (Adversary).** For certain state \( \psi_1 \in \Psi \) and a group of agents \( R_1 \) given the action series \( a_{1:t} \in \Lambda (action space) \) fulfilling task \( T \). Supposing without any interruption, the maximum teaming needs is \( max(N_1(\psi_1, a_{1:t}))). \) Considering another group of agents \( R_2 \) involving in reaction series \( a_{2:k} \). With interruption by \( R_2 \) group \( R_1 \)'s need is \( max(N_2(\psi_{12}, a_{12}))) \). If Eq. (5) is satisfied, it can be defined as \( R_2 \) an Adversary to \( R_1 \). In additional, if \( R_2 \)'s corresponding expected needs with \( (N_1) \) or without \( (N_2) \) involving \( R_1 \) are not equal, then \( R_2 \) will be regarded as Intentional Adversary (Eq. (6)). Otherwise, we consider \( R_2 \) as Unintentional Adversary (Eq. (7)).

\[
\max(N_1(\psi_1, a_{1:t})) > \max(N_1(\psi_{12}, a_{12}))) \quad (5)
\]
\[
\mathbb{E}(N_{21}|\psi_{21}, a_{2:k}) \neq N_2 \quad (6)
\]
\[
\mathbb{E}(N_{21}|\psi_{21}, a_{2:k}) = N_2, \quad i, j, k \in \mathbb{Z}^+ \quad (7)
\]

**3 Explore Domain Problem Statement**

In Explore Domain, \( \beta \) Explorers are exploring and collecting rewards (reaching treasure locations \( \rho_{tr} \)) in an uncertain environment. Intentional (\( \gamma \) Aliens) and unintentional (\( \gamma \) Obstacles) adversaries are randomly distributed in the scenarios. Explorer \( i \) and Alien \( j \) have strategy space \( S_{c_i} (s_1, \ldots, s_{n_i}); S_{a_j} (s_1, \ldots, s_{n_j}) \), \( i, j, n_i, n_j \in \mathbb{Z}^+ \), respectively. Also, every strategy has corresponding actions to execute \( s(a_1, a_2, \ldots, a_r), r \in \mathbb{Z}^+ \). \( C \) represents the explorers’ system costs in the entire process.
Supposing Explorer’s success probability (win rate) finding the treasure is \( W \). We model this problem as finding a set of suitable strategies \( S^*_e \) from \( S_e \), under the premise of maximizing \( W \) to minimize \( C \) based on basic teaming needs \( n_t \), after satisfying all the low-level needs in turn as Eq. (4). It can be described as an optimization problem formulating as Eq. (8).

\[
S^*_e = \text{arg}\max_{S_e} W(S_e|S_a, \gamma, \rho_{tr}) + \min \sum_{i=1,j=1}^{n,\nu} C_i(S_e_i|S_{a_i}, \gamma_i, N_{t_i})
\]

\[\text{s.t. } N_{t_i} \geq n_{t_e}, \forall i \in \alpha.\]

4 Approach

Fig. 2 outlines the structure of the Game-theoretic Utility Tree (GUT) and its computation units distributed in each level. First, the game-theoretic module (Fig. 2 (a)) calculates the Nash equilibrium based on the utility values \((u_{11}, \ldots, u_{nm})\) corresponding to each combination of strategy. Then, through the conditional probability (CP) module (Fig. 2 (b)), the CP of each situation can be described by \((p_1, \ldots, p_{nm})\), where \( p_{nm} = (p_m|p_{n-1}) \), \( i, 0, m \in Z^+ \).

**Here**, \( p_{n-1} \) and \( S_i \) present the probability of previous situation and current Game-theoretic state; \( s_{az}, s_0 \) and \( n, m \) represent their strategy space and size on both sides, respectively. In this section, we explain the decision-making process in GUT and describe the specific implementation in "explore domain".

4.1 GUT-based Decision-Making

For intentional adversaries, agents first decompose the specific goal into several independent subtasks based on the same category of individual low-level behaviors or atomic operations (basic group strategies) [Yang and Parasuraman, 2020]. Then, through calculating various Nash equilibrium based on different situation utility values in each level’s Game-theoretic Utility Computation Units, agents can get optimal or sub-optimal strategy sets tackling the current status according to Nash Existence Theorem and Bayesian Network Maximum A Posterior (MAP) Inference [Koller and Friedman, 2009].

**GUT** also can be regarded as a Task-Oriented Decision Tree. We formalize it as Theorem 1 and Corollary 1. The detailed proof is given in the supplemental material (Appendix. D).

**Theorem 1** (GUT Decision). Let \( A \) and \( B \) represent the groups of Explorers and Aliens. The simultaneous normal-form game representing the non-cooperative game between explorers and aliens is as a structure \( G=(\{A, B\}, \{S_e, S_a\}, \{N_{t_A}, N_{t_B}\}). \)

**Supposing** the GUT at the explorer group has \( w \) levels. \( G=(\{A, B\}, \{S_e, S_a\}, N_{t_A}, i \in w \) (Fig. 2).GUT describes corresponding zero-sum game in each level. Then, \( A \) has at least one dominant strategy series \((s_1, s_2, \ldots, s_w)\) in GUT.

**Corollary 1** (GUT MAP). **Supposing** the joint probability of solving a GUT is \( P(x) = P(x_1, x_2, \ldots, x_w) \). Assume we have a set of (exact or approximate) max-marginals \( \{\text{MaxMargin}(X_i)\}_{X_i \in \chi} \) in all of the computation units \( \chi \). Then, for each variable \( X_i \) (selected computation unit), there is a unique \( x_i^* \) that maximizes:

\[
x_i^* = \text{arg}\max_{x_i \in S(X_i)} \text{MaxMargin}(x_i)
\]
4.2 Unintentional Adversary Decision-Making

We design the *Adapting The Edge* algorithm for the unintentional adversaries. It can help agents tackle static unintentional adversaries and adapt their edge’s trajectory until it finds a suitable route to the goal point. Through sharing the communication data between agents, individuals can select the direction of less potential collision probability to move. In our scenarios, the two mountains represent the unintentional adversaries, and explorers need to find a path passing through them (See Appendix C for more details).

4.3 Explore Domain Implementation

In our game, the explorers group as *Patrol* formation (see Fig. 1) detecting the unknown world. After tackling various threats and adversaries, they always choose the shortest path to the goal point, then circle the treasure. In the whole process, explorers present a kind of global behaviors performing *Collective Rationality* and caring about *Group interest*. In contrast, aliens show *Self-interest* and do not cooperate (See Appendix A for relative definitions). For explorers, their *Teaming Needs* (expected utilities) is under the premise of maximizing the chance of finding the treasure to minimize HP cost based on fitting their low-level needs, such as safety and basic needs.

5 Experiments

We evaluate *GUT* from two different perspectives: *Interaction Experiments* compares the performance of explorers’ cooperative strategies between *GUT* and *QMIX*; *Information Prediction* demonstrates the *GUT* when different predictive models are implemented to estimate aliens’ states.

In experiments, we suppose each explorer has the same energy and HP levels initially, and every moving step will cost 0.015% energy. Every communication round and per time attacking will cost 0.006% and 0.01% energy, respectively. Aliens have 3x more capable than explorers in the attacks, and per time attacking will cost the explorers 0.15% HP. Their per time attacking energy and per time attacked HP cost are 0.03% and 0.05% (Appendix B shows more details about the experiment setting). The video demonstrating the experiments is available through an anonymous video hosting service at https://streamable.com/gty9am.

5.1 Interaction Experiments

We analyze *GUT* by simulating different cooperative styles and communication forms, comparing the performance with the state-of-the-art cooperative decision-making approach – *QMIX* [Rashid et al., 2018] as follows:

1) **GUT (NC) [Noncooperation + No Communication]** In this situation, explorers adopt *GUT* computing the winning rate based on its perceiving information, but no communication, which means that it does not get the consistency to attack or defend the specific alien (Appendix B – Fig. 7).

2) **QMIX [Partial Cooperation + Partial Communication]** *QMIX* [Rashid et al., 2018] is a state-of-the-art value-based method applied to reinforcement learning in MAS. Here, we only focus on the decision making part of *QMIX*, which considers the global benefit yielding the same result as a set of individual rewards. It allows each agent to participate in a decentralized execution solely by choosing greedy actions for its rewards. Accordingly, we assume that each explorer can cooperate, communicate, and share information with its observing explorers. Then through calculating the corresponding winning rate based on the number of its observing explorers and aliens, it chooses attacking or defending the specific *hp lowest* target (Appendix B – Fig. 8).

3) **GUT (PC) [Partial Cooperation + Partial Communication]** Here, we consider the same situation as *QMIX*, but explorers calculate the winning rate with *GUT* and get the consistency to attack or defend the *hp lowest* alien through partial communication (Appendix B – Fig. 9).
In these experiments, we do not involve Unintentional Adversary (obstacles) (Fig. 4) and consider three different proportions (A/E) between aliens and explorers as follow: 20 explorers vs 30 aliens, 25 explorers vs 25 aliens and 30 explorers vs 20 aliens. We assume that an agent can detect opponents’ current state in its perception range. For each scenario, we conduct ten simulation trials for each proportion with same environment setting. Fig. 3 shows that GUT (FC) has the best performance compared with other cases. The GUT (NC), QMIX, and GUT (PC) do not have much difference between explorer average HP cost results in Fig. 3(a), but in Fig. 3(b) num. of explorers lost for killing an alien and Fig. 3(c) HP cost for killing an alien, the QMIX and GUT (PC) show some advantage comparing with GUT (NC). For the winning rate comparison, Table. 4 also reflects the similar results.

**Results** This experiment shows that cooperation conduces to decrease the costs and boost the winning rate for more challenging tasks. More importantly, GUT can help agents representing more complex group behaviors and strategies, such as forming various shapes and separating different groups adapting adversarial environments in MAS cooperation. It vastly improves system performance, adaptability, and robustness. Besides, communication plays an essential role in cooperation, such as solving conflicts and getting consistency through negotiation. In GUT (NC) and QMIX, agents only share local information about the number of observing agents for naive attacking or defending behaviors. However, GUT (FC) present more complex relationships between agents’ cooperation by organizing global communication data.

**5.2 Information Prediction**

We design two kinds of perceiving models to analyze the individual and system performance in different scenarios. One is Complete Information, which means that if an agent can perceive the adversary, it will detect the opponent’s status, such as unit attacking energy cost and energy level. The other is Incomplete Information. It implies that the agent cannot gain opponents’ state in its observable range.

**Predictive Models** We implement two Machine Learning prediction models Linear (Eq. (11)) and Polynomial Regression (Eq. (12)), estimating adversaries’ status in Incomplete Information. We take regressors as individual unit cost $HP_{uc}$ and average system cost $HP_{asc}$ to predict opponent unit attacking energy cost $E_{uc}$ and current energy level $E_{el}$ respectively.

$$E_{uc} = HP_{uc} \times \beta_{uc} + \varepsilon;$$

$$E_{el} = 100 - HP_{asc} \times \beta_{asc} + \varepsilon.$$ (11)
(a) Explorer Average HP Cost
(b) Kill Per Alien - Explorer Lost
(c) Kill Per Alien - HP Cost

Figure 5: The Individual Explorer’s Performance with Different Predictive Models Only Intentional Adversary.

(a) Explorer Average HP Cost/w
(b) Explorer Average Energy Cost/w
(c) Explorer Average Loss/w

Figure 6: The Individual Performance with Different Predictive Models Considering Unintentional Adversary.

\[
E_{uc} = HP_{uc}^2 \cdot \beta_{uc_2} + HP_{uc} \cdot \beta_{uc_1} + \varepsilon;
\]

\[
E_{el} = 100 - HP_{asc}^2 \cdot \beta_{asc_2} - HP_{asc} \cdot \beta_{asc_1} + \varepsilon. \tag{12}
\]

Here, \(\beta\) is corresponding regression coefficients \(\beta_{uc,1,2} = \{0.08, 0.03, 0.0001\}, \beta_{asc,1,2} = \{0.03, 0.0003, 0.00001\}\), \(\varepsilon\) presents the error following the normal distribution \(N(0, 1)\).

1) With only intentional adversaries In this scenario, we consider five proportions of explorers and aliens (M/A) distributing in the map randomly. For each ratio, we also conduct ten simulation trials with the same experimental setting. From an individual perspective, Fig. 5 shows that Linear Regression model has more accuracy than Polynomial Regression model comparing with the result trend of Complete Information (ground truth). From system perspective (Table. 5), the winning rate and system average energy/HP cost with different predictive models also show the similar results.

2) With intentional and unintentional adversaries In this setting, we consider a more complex scenario, which involves the unintentional adversary (two mountains) and aliens adopting the QMIX to make their individual decision. We fix the number of explorers \(E=25\) and aliens \(A=25\) and conduct ten trials for each predictive model. Through the individual performance shown in Figs. 6(a) and 6(b), we notice that due to unintentional adversaries involved, individual average HP and energy cost for winning a round increase distinctly. Also, Fig. 6(c) shows that the entire group cost more agents to win a round concerning the obstacles involved. Table. 5 reveals similar conclusion that unintentional adversaries lead to the decrease of the winning rate and more system cost with the same condition for winning one round.

**Results** A suitable predictive model plays a vital role in shrinking biases or errors between the predictive results and ground truth through those experiments. More realistically, agents would face Incomplete Information scenarios to estimate opponents’ states from indirect information in adversarial environments. Furthermore, predictive models’ parameters also require adapting corresponding scenarios, which means agents need to learn from their experience or system performance adjusting parameters for the specific situation.

6 Conclusion and Future Work

We introduce a new network model called Game-theoretic Utility Tree (GUT) mimicking the agent decision-making process and the algorithm Adapting The Edge for MAS cooperation working in adversarial environments. We then presented a new Explore Domain evaluating GUT against the state-of-the-art cooperative decision-making approach QMIX. We demonstrated the effectiveness of GUT through two types of experiments including interaction and information prediction.

It will be essential for future work to improve GUT from different perspectives, such as optimizing GUT structure through learning from different scenarios, designing appropriate utility functions, building suitable predictive models, and estimating reasonable parameters fitting the specific scenario. Besides, implementing GUT in real robots is also an exciting and challenging problem helping us develop more robust computation models for MAS cooperation.
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Adversarial Environments: A Game-Theoretic Utility Network for Self-interest Partial Communication

B Experiment Setting

Full Communication In this status, agents always keep in touch with each other even when they are not in the sensing range. Also, the communication graph can be represented as a completely connected graph. It allows each agent to communicate and exchange data with its neighbor until the group reaches Information Equilibrium, which means that every group member has the same information for the entire group [Yang and Parasuraman, 2020].

Noncooperation The individual does not communicate with each other and makes decisions only depending on its needs. In this situation, the agent only concerns its benefits based on Self-interest.

Partial Cooperation Based on the Partial Communication information, individuals only cooperate with the observable group members to maximize their needs or minimize costs.

Full Cooperation According to the Full Communication data, individuals make decisions based on the Group-interest showing Collective Rationality.

C Unintentional Adversaries Decision

When explorers perceive the mountains (obstacles - static unintentional adversaries), they utilize limited information by sharing the perceiving information among agents for cooperative collision avoidance. Our experiments involve nine robots. In current situation (Fig. 11), robots R5 detect the mountain. To avoid a collision, it needs to switch the moving direction based on the tangent's direction of the nearest collision point $c$. There are two directions $n$ and $m$. According to the current status, $R5$ will select the direction $n$, which has more non-collision robots potentially.

Specifically, $L$ is a straight line passing through the tangent point $c$ and perpendicular to $n$ and $m$. There are four robots $R1$, $R2$, $R3$, and $R6$ without collision in the direction $n$ comparing with three non-collision robots $R7$, $R8$, and $R9$ in the direction $m$ in current situation. So $R5$ will move $\Delta t$ in direction $n$, then adjust the direction to the goal point moving forward until not unintentional adversaries in its route through iterating the process. Alg. 2 presents the decision process.

D Analysis and Proofs

D.1 Decision-making using GUT

Theorem 1 (GUT Decision). Let $A$ and $B$ represent the groups of Explorers and Aliens. The simultaneous normal-form game representing the non-cooperative game between explorers and aliens is a structure $G=\{(A, B), \{S_e, S_a\}, \{N_{t_A}, N_{t_B}\}\)$. Supposing the GUT at the explorer group has $w$ levels, $G_i(\{A, B\}, \{S_e, S_a\}, N_{t_A}), i \in w$ (Fig. 2 GUT) describes corresponding zero-sum game in each level. Then, $A$ has at least one dominant strategy series $(s_1, s_2, ..., s_w)$ in GUT.

Proof. For $w$-level GUT, supposing game $G_i$ in level $k$, the size of action space of group $A$ (the number of agent A is $z$) and $B$ are $l_i$ and $m_i$ correspondingly. For the intentional decision, the zero-sum game $G_i$ can be described as Eq. (1): $G_i = \{(A, B), \{S_e, S_a\}, N_{t_A}\}, i \in w$; (1)

Based on the teaming needs (Eq. (4)) definition, group A’s expected utilities $N_{t_A}$ can be presented as Eq. (2).

$$N_{t_A} = \sum_{i=1}^{w} E_i(U) = (u_{gk})_{l_i \times m_i}, \quad g \in l_i, k \in m_i, j \in z; \quad (2)$$

According to Nash Existence Theorem, it guarantees the existence of a set of mixed strategies for finite, non-cooperative games of two or more players in which no player can improve his payoff by unilaterally changing strategy [Weisstein, 2002]. So every finite game has a Pure Strategy Nash Equilibrium or a Mixed Strategy Nash Equilibrium. The process can be formalized as two steps.
Explorers exhibit global group behavior with GUT because of no cooperation within the team.

Explorers exhibit local group behavior with QMIX by partially cooperating with the explorers within their perception range.

Explorers exhibit no group behavior with GUT because of no cooperation within the team.

Explorers exhibit local group behavior with GUT by partially cooperating with the explorers within their perception range.

Explorers exhibit global group behavior with GUT by fully cooperating with all explorers.

Figure 7: GUT (NC)
Figure 8: QMIX
Figure 9: GUT (PC)
Figure 10: GUT (FC)

Figure 11: Illustration of "Adapt The Edge" algorithm for tackling (unintentional) obstacles.

Algorithm 2: Adapting The Edge

| Input: Explorers’ and Mountains’ states |
| Output: moving direction \( r \) and distance \( \Delta d \) |
|---|
| while The nearest collision point \( c \) != Null do |
| \[ | calculate the number \( n \) and \( m \) of non-collision agents in both side of the line \( l \) passing through \( c \) and perpendicular \( c \)’s tangent; |
| if \( n > m \) then |
| \[ r = n \] side in line \( l \); |
| \[ \Delta d = \text{one step of agent’s movement}; \] |
| else if \( n = m \) then |
| \[ \text{agent stop}; \] |
| else if \( n < m \) then |
| \[ r = m \] side in line \( l \); |
| \[ \Delta d = \text{one step of agent’s movement}; \] |
| return \( r = \) current position to goal point, \( \Delta d \) |

a. Compute Pure Strategy Nash Equilibrium
We can present agents’ utility matrix as Eq. (3):

\[
\begin{bmatrix}
  u_{11} & u_{12} & \cdots & u_{1m_1} \\
  u_{21} & u_{22} & \cdots & u_{2m_1} \\
  \vdots & \vdots & \ddots & \vdots \\
  u_{l1} & u_{l2} & \cdots & u_{lm_1}
\end{bmatrix}
\]

(3)

The row and column correspond to the utilities of agent \( A \) and \( B \) separately. We can compute the maximum and minimum values of the two lists separately by calculating each row’s minimum value and each column’s maximum value.

\[
\min_{1 \leq k \leq m_1} \max_{1 \leq g \leq l_i} u_{gk} = \max_{1 \leq g \leq l_i} \min_{1 \leq k \leq m_1} u_{gk}
\]

(4)

If the two value satisfy the Eq. (4), we can get the game \( G_i \) Pure Strategy Nash Equilibrium Eq. (5), and corresponding game value Eq. (6).

\[
\text{PSNE} = (A_*, B_\cdot); \quad V_{G_i} = u_{g_\cdot k_\cdot}.
\]

(5)

(6)

b. Compute Mixed Strategy Nash Equilibrium
The tactics’ probability of agent \( A \) present as Eq. (7).

\[
AX = (x_1, x_2, \ldots, x_{l_i});
\]

\[
\sum_{g=1}^{l_i} x_g = 1, x_g \geq 0, \quad g = 1, 2, \ldots, l_i.
\]

(7)

Similarly, we also can conclude agent \( B \) tactics’ probability as Eq. (8).

\[
BY = (y_1, y_2, \ldots, y_{m_1});
\]

\[
\sum_{k=1}^{m_1} y_k = 1, y_k \geq 0, \quad k = 1, 2, \ldots, m_1.
\]

(8)

We define \( (X, Y) \) as Mixed Situation in certain status. Then, we can deduce the expected utility of agent \( A \) and \( B \) Eq. (9) and (10) respectively.

\[
E_A(X, Y) = \sum_{g=1}^{l_i} \sum_{k=1}^{m_1} u_{gk} x_g y_k = E(X, Y);
\]

(9)

\[
E_B(X, Y) = -E(X, Y)
\]

(10)

In the Game \( G_i \), if we get all the Mixed Tactics of agent \( A \) and \( B \) as Eq. (11) and (12), we can deduct the \( G_i \)’s Mixed Expansion as Eq. (13). Furthermore, if a tactic \( (X^*, Y^*) \) satisfies Eq. (14) and (15), we define the tactic as the optimal strategy (Eq. (16)) in current state.

\[
S^*_c = AX;
\]

(11)

\[
S^*_c = BX;
\]

(12)

\[
G^*_i = \{ S^*_c, S^*_c, E \};
\]

(13)

\[
E(X^*, Y) \geq V_{S^*_c}, \quad \forall Y \in S^*_c;
\]

(14)

\[
E(X, Y^*) \leq V_{S^*_c}, \quad \forall X \in S^*_c;
\]

(15)

\[
V_{S^*_c} = V_{G_i} = V_{S^*_c}.
\]

(16)

As the above discussion, we express the GUT computation process as corresponding Probabilistic Graphical Models [Koller and Friedman, 2009] – Bayesian Network.
Supposing each node is independent, the total number of nodes \( N \) and the current joint probability distribution of the group \( A \) in the GUT can be represented as Eq. (17) and (18).

\[
N = N_1 + N_2 + \ldots + N_w
\]

\[
= 1 + l_1 \times m_1 + (l_1 \times l_2) \times (m_1 \times m_2) + \ldots
+ (l_1 \times l_2 \times \ldots \times l_{n-1}) \times (m_1 \times m_1 \times \ldots \times m_{w-1})
\]

(17)

\[
P(X) = P(X_1, X_1, \ldots, X_N)
\]

\[
= P(X_1)P(X_2|X_1)\ldots P(X_N|X_1, X_2, \ldots, X_{N-1})
\]

\[
= \prod_i P_i(X_i|\text{Par}\_G(X_i)), \ i \in N
\]

(18)

Since Nash Existence Theorem guarantees that every game has at least one Nash equilibrium [Jiang and Leyton-Brown, 2009], we get Eq. (19).

\[
P_i(X_i) \neq 0 \implies \prod_i P_i(X_i|\text{Par}\_G(X_i)) = P(X) \neq 0
\]

(19)

**Low Bound**  If each level Nash Equilibrium calculation in the GUT is the Pure Strategy Nash Equilibrium, the individual agent can obtain a unique tactic entering into the next level, which means the tactic’s probability is equal to one (Eq. (20)). We also can get corresponding dominant strategy set \((s_1, s_2, \ldots, s_n)\) in GUT.

\[
P_i(X_i) = 1 \implies \prod_i P_i(X_i|\text{Par}\_G(X_i)) = P(X) \equiv 1
\]

(20)

**Corollary 1** (GUT MAP). *Supposing the joint probability of solving a GUT is \( P(x) = P(x_1, x_2, \ldots, x_w) \). Assume we have a set of (exact or approximate) max-marginals \( \{\text{MaxMarg}\_P(X_i)\} \) \( X_i \in X \) in all of the computation units \( \chi \). Then, for each variable \( X_i \) (selected computation unit), there is a unique \( x_i^* \) that maximize:

\[
x_i^* = \arg \max \text{MaxMarg}_P(x_i)
\]

(21)

**Proof.** We can simplify an \( w\)-level GUT as one link Bayesian Network (Fig. 12).

![Figure 12: w-level GUT as one link Bayesian Network.](image)

Now, we get the factors of product Eq. (22) (\( \phi_x \) are the intermediate factors). So the maximum joint probability of GUT Decision is equal to get its maximum factors of product. Then through VE (Variable Elimination) [Koller and Friedman, 2009], we can get the MAP assignment of this GUT. The entire process has two steps: 1) Variable elimination Eq. (23); 2) Tracing back to get a joint assignment \((x_1^*, x_2^*, \ldots, x_w^*)\) Eq. (24). Finally, we can get MAP results of the GUT Eq. (25).

\[
P(x) = \prod_i P_i(x_i|\text{Par}\_G(x_i)) = \prod_i \phi_{x_i} \implies \max P(x) = \max \prod_i \phi_{x_i}
\]

(22)

**Variable Elimination**

if \( X \in \text{Scope}[\phi_x] \) then \( \max(\phi_{x_i}, \phi_{x_i+1}) = \phi_{x_i} \max(\phi_{x_i+1}) \)

\[
\implies \text{first elimination :}
\]

\[
\max P(x) = \max_{x_2, x_3, \ldots, x_w} \phi_{x_2}\phi_{x_3}\ldots\phi_{x_w} \max \phi_{x_1}
\]

second elimination:

\[
\max P(x) = \max_{x_3, x_4, \ldots, x_w} \phi_{x_3}\phi_{x_4}\ldots\phi_{x_w} \max \phi_{x_2} \tau_1
\]

\[
\ldots
\]

(23)

**(w)**ith elimination:

\[
\max P(x) = \max_{x_w} \tau_{w-1}
\]

**Tracing Back**

\[
x_w^* = \arg \max \psi_w(x_w)
\]

\[
x_{w-1}^* = \arg \max \psi_w(x_w, x_{w-1})
\]

\[
\ldots
\]

\[
x_1^* = \arg \max \psi_1(x_w, x_{w-1}, \ldots, x_1)
\]

(24)

**Maximum A Posterior**

\[
x^* = (x_1^*, x_2^*, \ldots, x_w^*) \text{ is the MAP assignment,}
\]

\[
\tau_{w-1} \text{ is the probability of the most probable assignment.}
\]

(25)

**E The Definitions in Experiments**

In our experiments, we assume that explorers and aliens have the same moving speed, and aliens can not share information. Sec. E.4 lists terms and notations used in this subsection. We implement the first two levels of agent needs hierarchy (safety needs - Health and basic needs - Energy). Capability needs and teaming needs are not implemented in this paper.

**E.1 Winning Utility Expectation**

We consider using Winning Probability following Bernoulli Distribution to represent individual high-level expected utility (teaming & cooperation needs) in the first level (Eq. (26)).

\[
W(t_{ev}, t_{mv}, r_{ev}, r_{mv}, n, m) = \left( a_1 t_{ev} + a_2 t_{mv} + a_3 r_{ev} + a_4 t_{mv} r_{ev} + a_5 r_{mv} \right)^n;
\]

(26)
E.2 Energy Utility Expectation

The second level’s utility can be described as the relative Expected Energy Cost (Eq. (27), (28), (29) and (28)), which consists of three parts of energy costs: moving, attacking, and communication.

\[
E(d, v, f, q, n, m, \phi_e, \phi_m) = b_0 + b_1 \int_{-\infty}^{+\infty} (n - m)e_d(x)p_d(x, d)dx \\
+ b_2 \sum_{i=1}^{+\infty} ne_a_i(i, f)p_m(j, m\phi_m) - \sum_{j=1}^{+\infty} me_a_m(j, q)p_a(i, n\phi_e)) \\
+ b_3 \sum_{w=1}^{+\infty} ne_c(w)p_e(w, \frac{d}{v}); \tag{27}
\]

In the lowest level, we use the expected HP cost to describe E.3 HP Utility Expectation

\[
h(x, y, z) = \rho z(x + y) \tag{37}
\]

\[
t_{e,m}(e_{e,m}) = \gamma_{e,m}e_{e,m}; \tag{38}
\]

\[
r_{e,m}(e_{e,m}) = \delta_{e,m}e_{e,m}; \tag{39}
\]

\[
p_{h_e}(i, \phi_e) \text{ and } p_{h_m}(j, \phi_m) \text{ can be similarly described as formulas Eq. (32) and (33) correspondingly. Then, through simplifying the Eq. (36), we finally get Eq. (40).}
\]

\[
H(k, t_e, t_m, r_e, r_m, g, \phi_e, \phi_m) = c_0 + c_1 \rho[k\phi_m e_c(\gamma_e + \delta_e) - g\phi_e e_m(\gamma_m + \delta_m)]; \tag{40}
\]

E.4 Notations used in Sec. E

- \(AT\) and \(BT\) present the action space of group A and B correspondingly;
- \(n\) and \(m\) present the number of Explorers and Aliens respectively;
- \(d\) presents the group average distance between two opponents;
- \(v\) presents the agent’s velocity;
- \(i\) and \(j\) present the times of attacks and being attacked;
- \(w\) presents Explorers’ communication times;
- \(f\) and \(q\) present the unit attacking energy cost of both sides agents respectively;
- \(t_{ev}\) and \(t_{mv}\) present average attacking ability levels of both sides respectively;
- \(r_{ev}\) and \(r_{mv}\) present average defending ability levels of both sides respectively;
- \(t_e\) and \(t_m\) present specific agent’s attacking ability levels of both sides respectively;
- \(r_e\) and \(r_m\) present specific agent’s defending ability levels of both sides respectively;
- \(\phi_e\) and \(\phi_m\) present individual agent’s size;
- \(k\) presents the number of Explorers’ attacking simultaneously;
- \(g\) presents the number of Aliens’ attacking simultaneously;
- \(a, b, c, \rho, \gamma\) and \(\delta\) present corresponding coefficient;
- \(e_e\) and \(e_m\) present the current energy level of Explorer and Alien;
- \(h\) presents the current \(HP\) level of agent;
- \(p\) presents the probability corresponding to the different section.