Multiagent Bidirectionally-Coorinated Nets for Learning to Play StarCraft Combat Games

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Outline

Setting

- N agents and M opponents
- S denotes the state space of the current game, shared among all the agents
- $A_i = A$ is the action space of the controlled agent i for $i = 1, 2, ..., N$
- $B_i = B$ is the action space of the enemy i for $i = 1, 2, ..., M$
- $T : S \times A^N \times B^M \rightarrow S$ is the deterministic transition function of the environment
- $R_i : S \times A^N \times B^M \rightarrow R$ is the reward function of agent/enemy i for $i = 1, 2, ..., N + M$
- $\boldsymbol{a}_\theta : S \rightarrow A^N$ is the deterministic of controlled agents
- $\boldsymbol{b}_\phi : S \rightarrow B^M$ is the deterministic of enemies

Combat with Global Reward

- Each agent in the same team shares the same reward
- Reward of Agents Definition:

$$r(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) = \frac{1}{M} \sum_{j=N+1}^{M} \Delta R_j^t(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) - \frac{1}{N} \sum_{i=1}^{N} \Delta R_i^t(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) \tag{1}$$

where $\Delta R_j^t(\cdot) = R_j^{t-1}(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) - R_j^t(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b})$

- Reward of Enemies is the opposite, making the sum of rewards from both camps euqlling to zero.
- Minimax game:

$$Q^*(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) = r(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) + \lambda \max_{\theta} \min_{\phi} Q^*(\boldsymbol{s'}, \boldsymbol{a}_\theta(\boldsymbol{s'}), \boldsymbol{b}_\phi(\boldsymbol{s'})) \tag{2}$$

where $\boldsymbol{s'} = \boldsymbol{s}^{t+1}$

Proposed Multiagent Actor-Critic with Individual Reward

- Considering team collaboration
- Each agent's local reward:

$$r_i(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) = \frac{1}{|j|} \sum_{j=N+1 \bigcap \text{top-K(i)}}^{M} \Delta R_j(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) \tag{3}$$

$$- \frac{1}{|i'|} \sum_{i'=1 \bigcap \text{top-K(i)}}^{N} \Delta R_{i'}(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) \tag{4}$$

Model Architecture

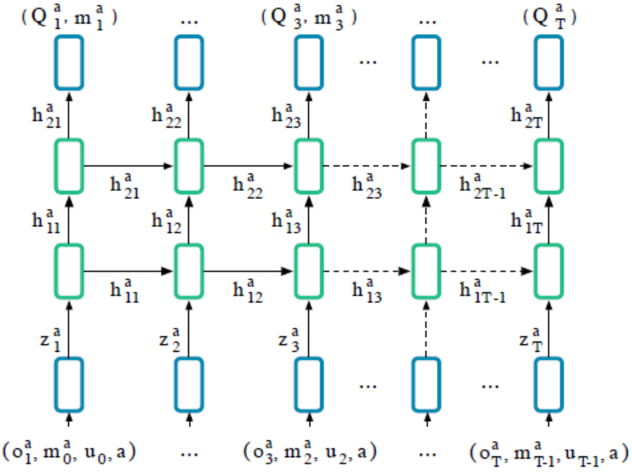


Figure 2: DIAL architecture.

Model Architecture

- Input: $(o_t^a, m_{t-1}^{a'}, u_{t-1}^a, a)$
- Embedding:
  $z_t^a = f_1(o_t^a) + f_2(m_{t-1}) + f_3(u_{t-1}^a) + f_4(a)$
  where f_1 is a task-specific network, f_2 is a 1-layer MLP and f_3 and f_4 are lookup tables
- 2-layer RNN with GRUs
- Output: Q_t^a, m_t^a

Algorithm(DIAL)

Initialise θ_1 and θ_1^-
for each episode e **do**
 s_1 = initial state, $t = 0$, $h_0^a = \mathbf{0}$ for each agent a
 while $s_t \neq$ terminal **and** $t < T$ **do**
  $t = t + 1$
  for each agent a **do**
   Get messages $\hat{m}_{t-1}^{a'}$ of previous time-steps from agents m' and evaluate C-Net:
   $Q(\cdot), m_t^a = \text{C-Net}\left(o_t^a, \hat{m}_{t-1}^{a'}, h_{t-1}^a, u_{t-1}^a, a; \theta_i\right)$
   With probability ϵ pick random u_t^a, else $u_t^a = \max_a Q\left(o_t^a, \hat{m}_{t-1}^{a'}, h_{t-1}^a, u_{t-1}^a, a, u; \theta_i\right)$
   Set message $\hat{m}_t^a = \text{DRU}(m)$, where $\text{DRU}(m) = \begin{cases} \text{Logistic}(\mathcal{N}(m_t^a, \sigma)), \text{ if training, else} \\ \mathbb{1}\{m_t^a > 0\} \end{cases}$
  Get reward r_t and next state s_{t+1}
 Reset gradients $\nabla\theta = 0$
 for $t = T$ **to** $1, -1$ **do**
  for each agent a **do**
   $y_t^a = \begin{cases} r_t, \text{ if } s_t \text{ terminal, else} \\ r_t + \gamma \max_u Q\left(o_{t+1}^a, \hat{m}_t^{a'}, h_t^a, u_t^a, a, u; \theta_i^-\right) \end{cases}$
   Accumulate gradients for action:
   $\Delta Q_t^a = y_t^a - Q\left(o_j^a, h_{t-1}^a, \hat{m}_{t-1}^{a'}, u_{t-1}^a, a, u_t^a; \theta_i\right)$
   $\nabla\theta = \nabla\theta + \frac{\partial}{\partial\theta}(\Delta Q_t^a)^2$
   Update gradient chain for differentiable communication:
   $\mu_j^a = \mathbb{1}\{t < T-1\} \sum_{m' \neq m} \frac{\partial}{\partial \hat{m}_t^a}\left(\Delta Q_{t+1}^{a'}\right)^2 + \mu_{t+1}^{a'} \frac{\partial \hat{m}_{t+1}^{a'}}{\partial \hat{m}_t^a}$
   Accumulate gradients for differentiable communication:
   $\nabla\theta = \nabla\theta + \mu_t^a \frac{\partial}{\partial m_t^a}\text{DRU}(m_t^a)\frac{\partial m_t^a}{\partial\theta}$

, , $\theta_{i+1} = \theta_i + \alpha\nabla\theta$
 Every C steps reset $\theta_i^- = \theta_i$

Experiment: Switch Riddle

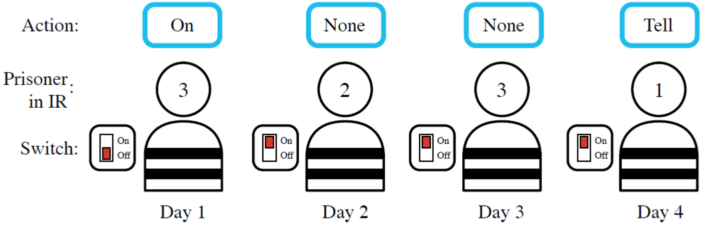
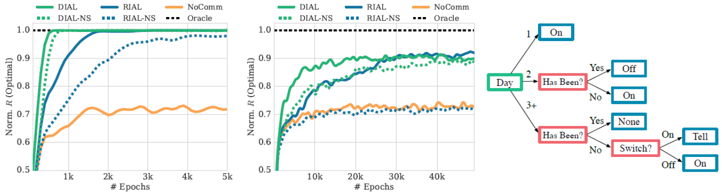


Figure 3: *Switch:* Every day one prisoner gets sent to the interrogation room where he sees the switch and chooses from “On”, “Off”, “Tell” and “None”.

Experiment: Switch Riddle

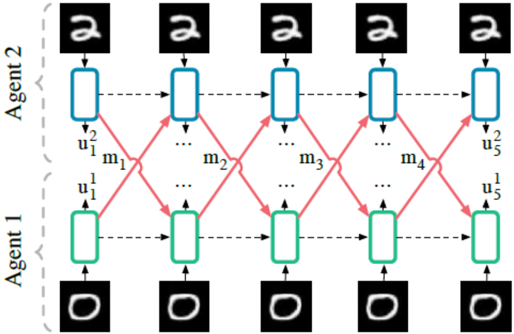
- $m_t^a, o_t^a \in \{0, 1\}$
- $u_t^a \in \{None, Tell\}$
- $r_t \in \{-1, 0, 1\}$
- Results:



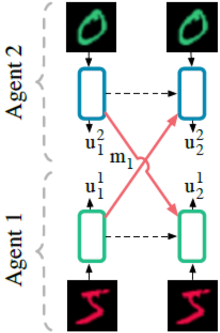
(a) Evaluation of $n = 3$ (b) Evaluation of $n = 4$ (c) Protocol of $n = 3$

Figure 4: *Switch:* (a-b) Performance of DIAL and RIAL, with and without (-NS) parameter sharing, and NoComm-baseline, for $n = 3$ and $n = 4$ agents. (c) The decision tree extracted for $n = 3$ to interpret the communication protocol discovered by DIAL.

Experiment: Multi-Step MNIST



Experiment: Colour-Digit MNIST



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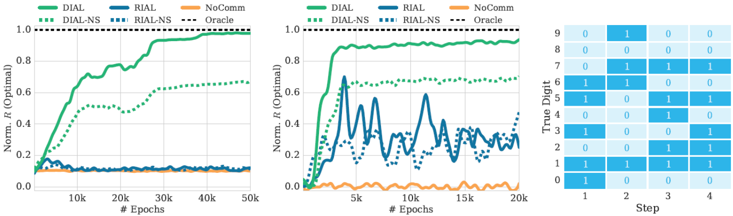
MNIST results



(a) Evaluation of Multi-Step (b) Evaluation of Colour-Digit (c) Protocol of Multi-Step

Figure 6: *MNIST Games:* (a,b) Performance of DIAL and RIAL, with and without (-NS) parameter sharing, and NoComm, for both MNIST games. (c) Extracted coding scheme for multi-step MNIST.

Reference

Reference:
[1] Jakob N. Foerster, Yannis M. Assael, Nando de Freitas, Shimon Whiteson; Learning to Communicate with Deep Multi-Agent Reinforcement Learning