从维度分析视角重新审视多智能体强化学习中的通信效率问题

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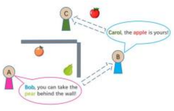
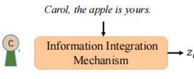
研究背景：

- **问题：**通信效率是实现多智能体协作的重要瓶颈。
- **关键发现：**现有通信方法多关注前两步，主要在消息层面优化内容、时机和对象。然而，我们发现，即使完成这些优化，在第三步整合消息时仍存在维度冗余与混杂因素。

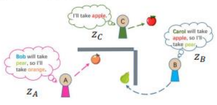
Step 1: Observing the Environment and optimizing the communication contents.



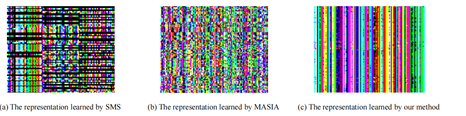
Step 2: Selecting timing and partners for communication.



Step 3: Integrating incoming messages to understand the environment and intentions of teammates.

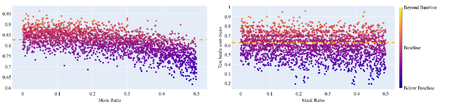


Step 4: Cooperative decision-making.



(a) The representation learned by SMS (b) The representation learned by MASIA (c) The representation learned by our method

Figure 2: The visualizations depict the representations learned by SMS[48], MASIA[11] and our method on a challenging SMAC task, 1o_2r_vs_4r. The learned features are projected into an RGB color image, where distinct colors indicate different feature types. The horizontal axis corresponds to feature dimensions, while the vertical axis represents samples from different trajectories. Greater color contrast signifies lower similarity between feature dimensions. These plots illustrate the similarity between dimensional features within a batch. In contrast to existing approaches, our method employs a redundancy-reduction technique that efficiently decouples the received information into distinct dimensions. Each of these dimensions represents a unique part of the information's entropy, ensuring that the resulting representation is both more informative and less redundant.



(a) MASIA (b) SMS

Figure 3: Experimental scatter plots were generated by MASIA and SMS with randomly masked dimensions on a challenging SMAC task, 1o_2r_vs_4r. The Baseline and the red dashed lines indicate the performance achieved by the unmasked representation of MASIA and SMS. Each point represents an independent experimental result, obtained by applying a specific mask rate to the original representation at the dimensional level. Notably, the original representation remains unchanged throughout the experiments. These results demonstrate the pervasive presence of dimensional confounders in the process of multi-agent communication.

创新方法（DMRAC框架）：

- **维度去冗余：**

$$\mathcal{L}_{RR} \triangleq \underbrace{\sum_i (1 - C_{ii})^2}_{\text{invariance term}} + \underbrace{\lambda \sum_i \sum_{j \neq i} C_{ij}^2}_{\text{redundancy reduction term}} \qquad C_{ij} \triangleq \frac{\sum_b z_{b,i}^A z_{b,j}^B}{\sqrt{\sum_b \left(z_{b,i}^A\right)^2} \sqrt{\sum_b \left(z_{b,j}^B\right)^2}}$$

- **维度去混淆：** $\tilde{z}_i^t = z_i^t \otimes \omega_i^t$

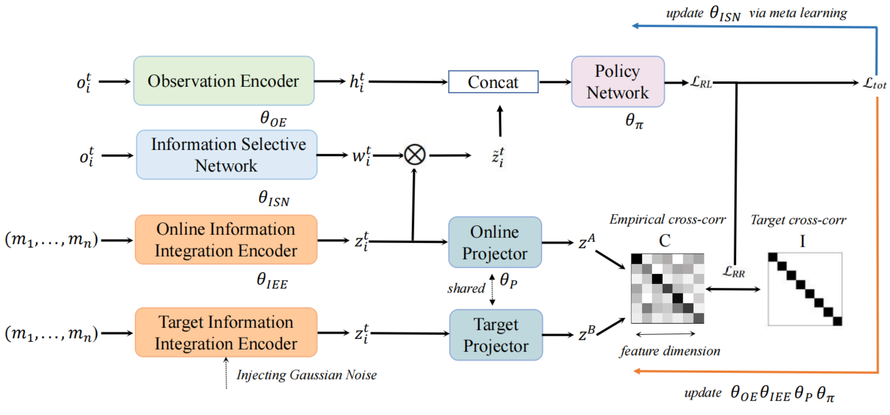


Figure 4: The overview of our proposed DRMAC.

性能突破：

- DRMAC在SMAC等多个任务中实现了显著的性能提升

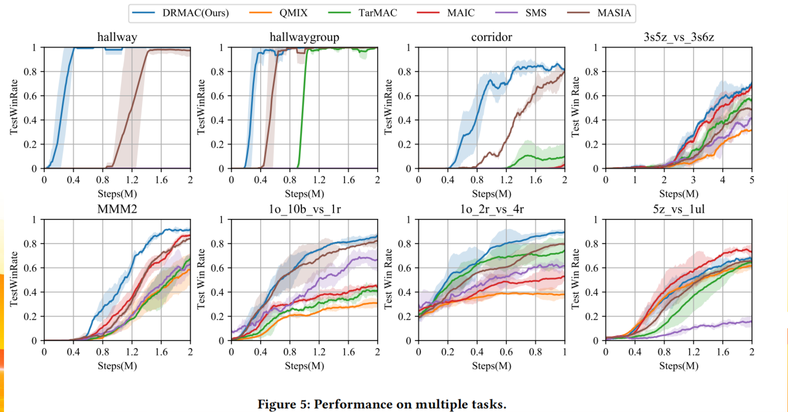


Figure 5: Performance on multiple tasks.