Learning to use a pre-defined language: Training a Communication Policy



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Joint Intrinsic Motivation

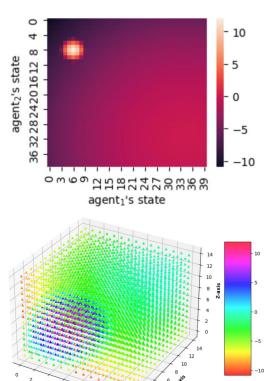
Re-Submission



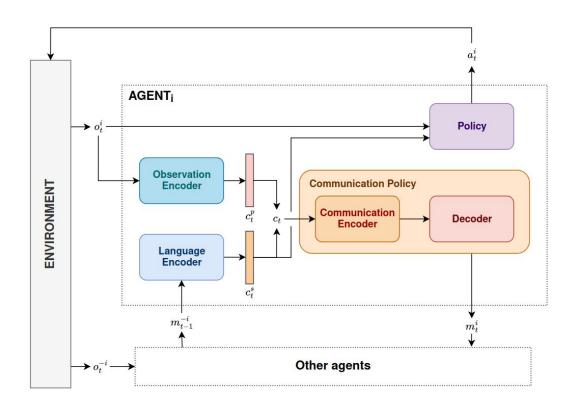
Goal: re-submission to AAMAS, with:

- Scenario with 4 agents:
 - → rel_overgen, playing with hyperparameters:
 - state dimension,
 - ε-greedy exploration probability,
 - size of reward spike.

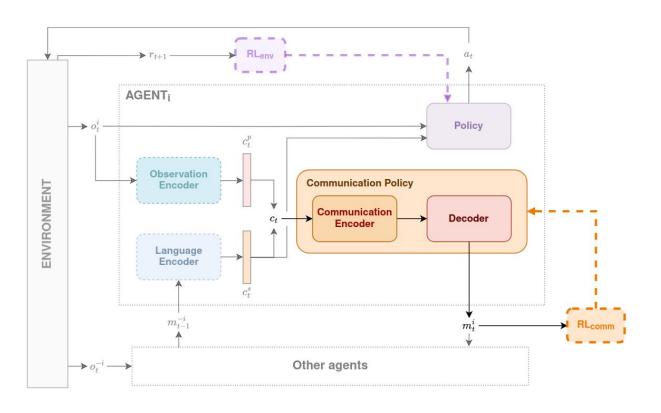
- Extended explanation of scalability in paper







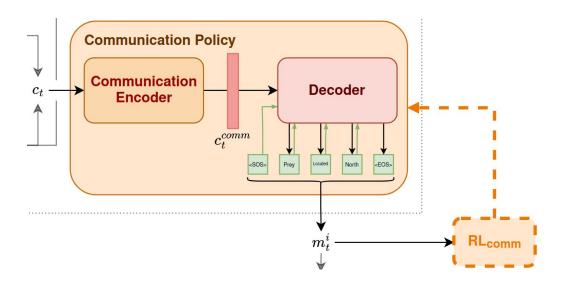




Communication Policy

Training policy





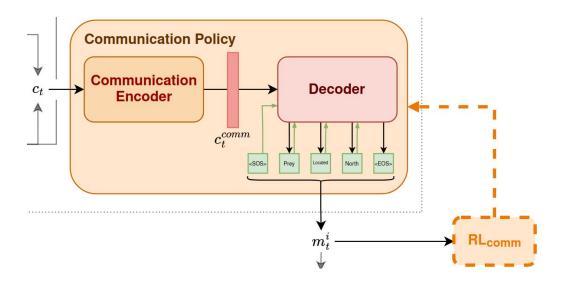
Training communication with PPO:

- **Task:** Generating messages (sequences of tokens)
- States: previous token
- Actions: next token

Communication Policy

Communication Encoder





Communication Encoder:

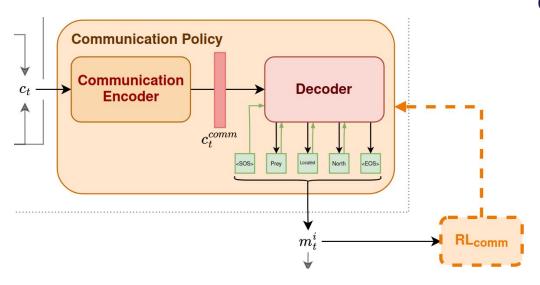
- MLP
 - single step as input
 - stack of steps as input
- RNN
- **Hierarchical** (Jaques 2019, Saleh 2020)

^[1] Jaques et al., Way Off-Policy Batch Deep Reinforcement Learning of Implicit Human Preferences in Dialog, 2019.

Communication Policy

Evaluating communication quality





Communication Evaluation:

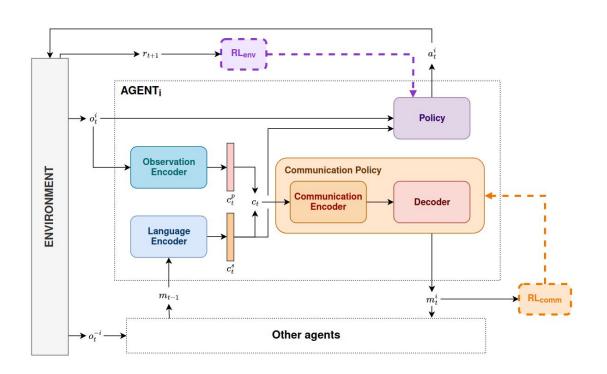
- Task performance: Reward from environment
- Language drifting: Penalty for diverging too much from pre-trained decoder (Ouyang2022)

- **Efficient communication:** Penalty for each token generated
- **Sharing valuable information:** Reward for adding information to a shared-memory
- Impacting other agents: maximizing information gain, wonderful life...

- ..

Training issue





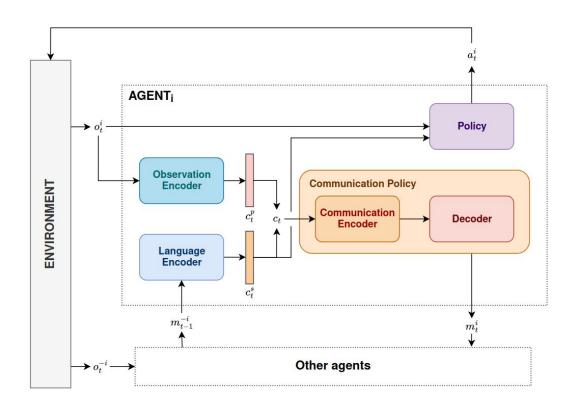
Two Parallel Training Loops:

Act Loop: RL from environment reward trained after each episode

VS.

Communication Loop: RL from communication quality trained after each step

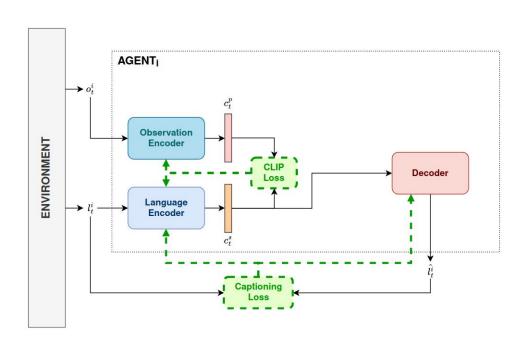




Training Process

Phase 1: Learning to ground and generate language





CLIP Loss

With the Observation Encoder $\omega: \mathbb{R}^N \to \mathbb{R}^M$, and the Language Encoder $\lambda: \mathbb{R}^{L \times V} \to \mathbb{R}^M$,

the grounding objective is:

$$J(\theta_{\omega}, \theta_{\lambda}) = max[cosim(\omega(o_k), \lambda(l_k))]$$



Captioning Loss

With the Language Encoder $\lambda: \mathbb{R}^{L \times V} \to \mathbb{R}^{M}$, and the Decoder $\delta: \mathbb{R}^{M} \to \mathbb{R}^{L \times V}$,

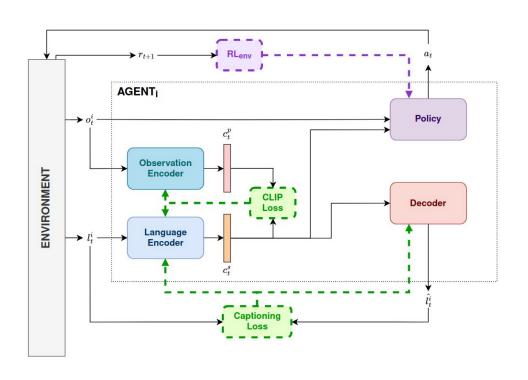
the captioning objective is:

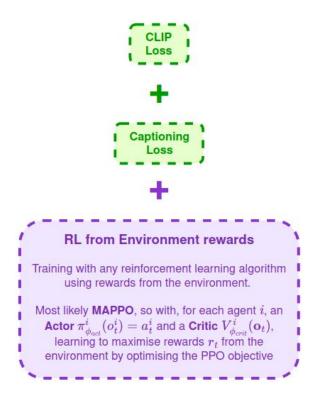
$$J(heta_{\lambda}, heta_{\delta}) = min \left[rac{1}{N}\sum_{i=0}^{N}(\hat{l_i}-l_i)^2
ight]$$

Training Process

Phase 2: Learning a working policy with "perfect messages"



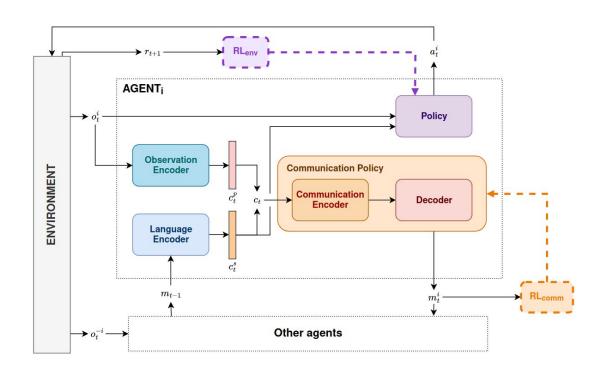




Training Process

Phase 3: Learning the communication policy







RL from Communication quality

We train a Communication Encoder

 $\mathbb{C}:\mathbb{R}^{2M} o \mathbb{R}^M$ to learn to choose which information to share, and we fine-tune the **Decoder** δ (pre-trained on captioning) to generate useful messages.

The reward for communication quality can be defined as,

$$r_t^{comm} = r_t - eta \log \left(rac{\delta_{FT}}{\delta_{PT}}
ight) + \ldots$$

with δ_{FT} the current fine-tuned version of the decoder and δ_{PT} the pre-trained version of the decoder with fixed parameters. We use PPO for learning the communication policy.



Fixed parameters

Next steps



- JIM:
 - Get working runs with 4 agents
 - Finish paper
- Communication policy
 - Dev communication evaluation
 - Move to BabyAl environment
 - Experiment with Communication Policy
 - Write paper

AAMAS 2024 deadline: October 9th

Thank you for you attention!

Questions?