Language-Grounded Multi-Agent Learning

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Table of Content

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    - Présenter le plan
    - Montrer l’avancement
- Représenter les forces qu’on veut montrer
- Pour chaque force
    - Définir
    - Proposer une méthode
    - Si possible montrer des résultats
    - Si possible montrer des vidéos d’éval
-

Jury de la soutenance

- Rang A
  - Olivier Simonin (Lyon) -- examinateur (et président?)
  - Sylvain Chevallier (Orsay) -- rapporteur?
  - (OU Yann Chevaleyre (Dauphine) mais pas rapporteur)
- Rang B
  - Clément Moulin Frier (Bordeaux) -- rapporteur
  - Alain Dutech (Nancy) -- rapporteur?
  - Aurélie Beynier (SU) -- examinatrice (et représentante SU)
  - ...? (hors SU)
  - Michael Defoort ? (vraiment pas RL) https://gdr-macs.cnrs.fr/node/1295 https://scholar.google.co.il/citations?user=vy6pLsgAAAAJ&hl=en

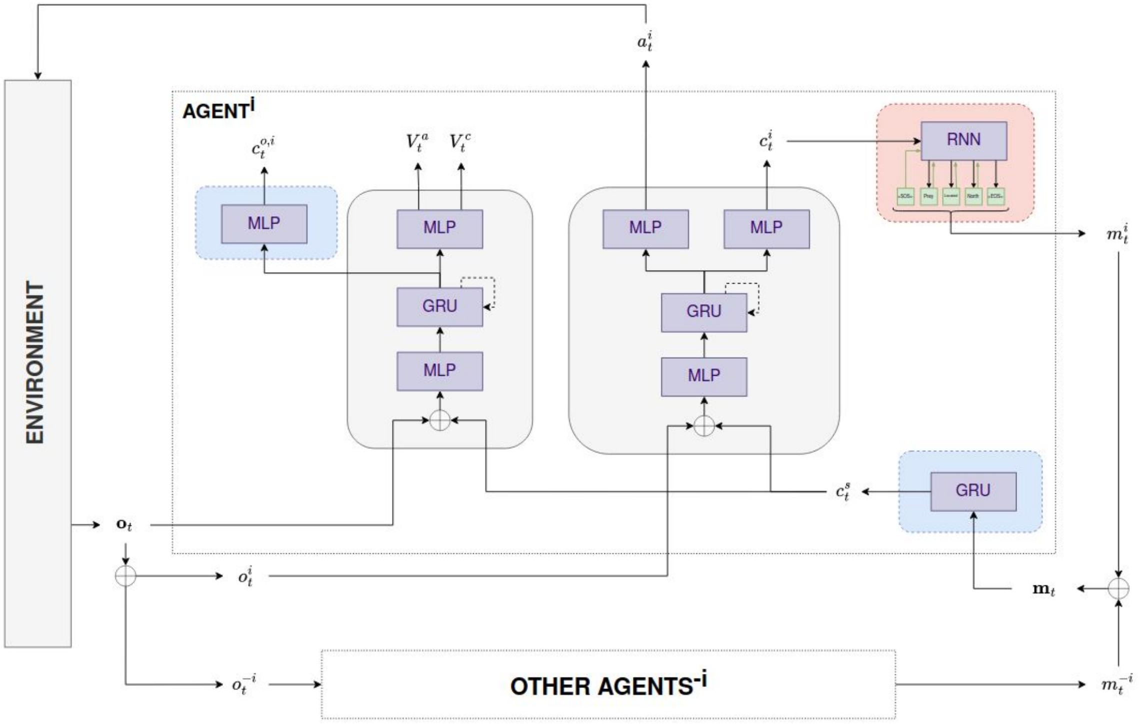
Olivier Simonin (A, président)
Sylvain Chevallier (A, examinateur) OU Yann Chevaleyre (A, examinateur)
Clément Moulin-Frier (B, rapporteur)
Alain Dutech (B, rapporteur)
Aurélie Beynier (B, examinatrice)

Manuscrit

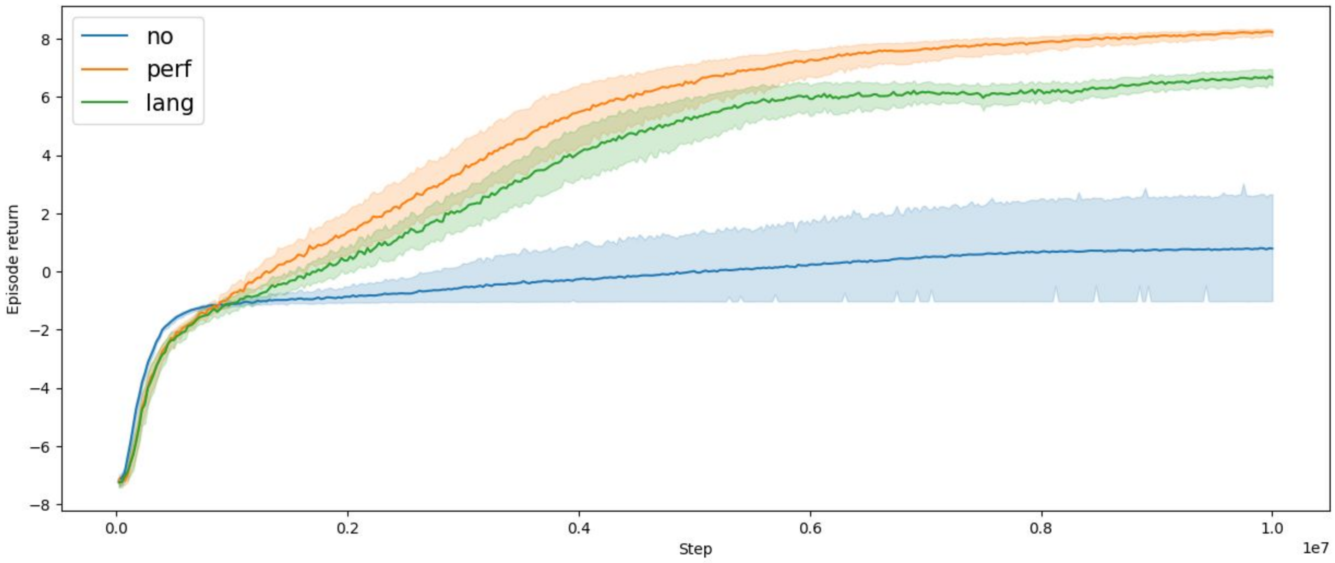
- Intro
- Chapitre 1: Reinforcement learning (definitions and overview)
  - [DONE] Overview of domain and trends
  - [DONE] Elements of RL
  - [DONE] Basic RL algorithms
  - [(almost) DONE] Neural networks
  - Deep RL
- Chapitre 2: Multi-agent Deep RL
  - Multi-agent systems (definitions)
  - Issues in MAS
  - Deep MARL algorithms
- [(almost) DONE] Chapitre 3: JIM
- Chapitre 4: Language-Grounded MARL
- Chapitre 5 ?

Language-Grounded Multi-Agent Learning

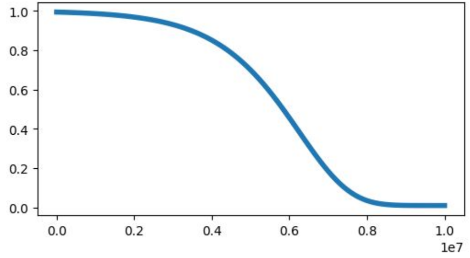
Arctor-Communicator-Critic archi



Initial results



no = No communication
perf = Perfect messages generated by Parser
lang = Learnt communication, with ε-perfect communication →



Experiments

Objectives

Show the advantages of using language

- Adaptation
- Universality
- Interpretability
- Interaction
- Language as a learning tool

Experiments

Adaptation

- To a more difficult setup

  Change the task slightly to make it more difficult

  Examples:

  - PredatorPrey: Make map larger
  - PredatorPrey: Make preys move faster/go away from predators
  - Make observation range smaller

- To a different task

  Put trained agents in a different task

  Examples:

  - PredatorPrey->Foraging (F->PP)
  - PredatorPrey->PreyPredator

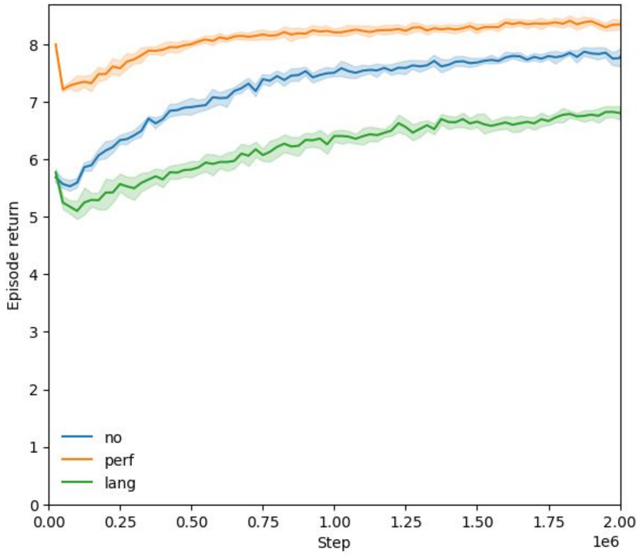
- To a new environment

Experiments

Adaptation: To a more difficult task

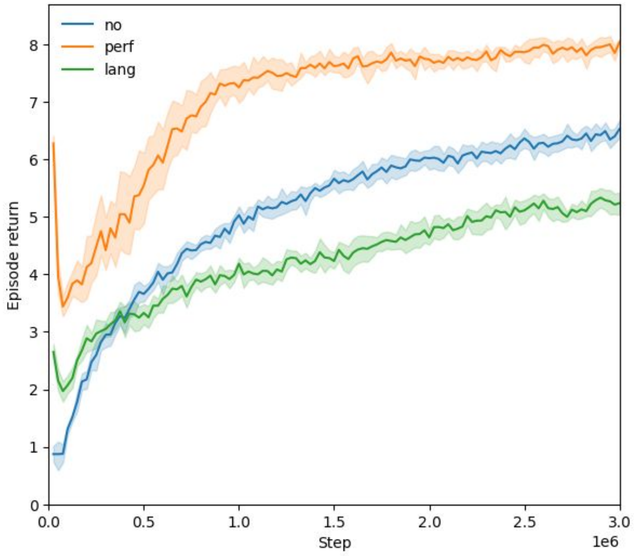
PredatorPrey, larger map

adapted from the best pre-trained runs



12x12

8 runs each



15x15

8 runs each (except perf 4)

Experiments

Universality

- Communicating with agents never seen before

  Train two sets of agents, then evaluate a mix of the two groups

Experiments

Interpretability

- Try to understand messages given states (emergent vs language)
- Try to play the role of an agent, dealing with generated messages of other agents

Experiments

Interaction

- Send messages in the message canal and analyse reaction

- Play as an agent, being able to send messages

Experiments

Language as a learning tool

- Compare: agents trained with perfect language modules since the beginning

  vs agents trained by learning language modules at the same time

Issues with emergent communication

- Continuous emergent communication does not work when generated as an action learnt with RL
- In literature, communication is learnt as a module inside the RL agent

=> Try method similar to literature

=> Try discrete-action messages

Next steps

- Make better emergent communication
- Re-try Foraging and try to make it work
- Do experiments
- Write manuscript

Thank you for you attention !

Questions ?