Deep Interactive Bayesian RL via Meta-Learning



Luisa Zintgraf, Sam Devlin, Kamil Ciosek, Shimon Whiteson, Katja Hofmann

Context

Question:

How can agents adapt to initially unknown other agents, while maximising online return?

Solution (in principle):

Interactive Bayesian RL (IBRL) [1]. Idea: Maintain belief over other agents, and compute optimal action under uncertainty. But: IBRL is intractable for most problems.

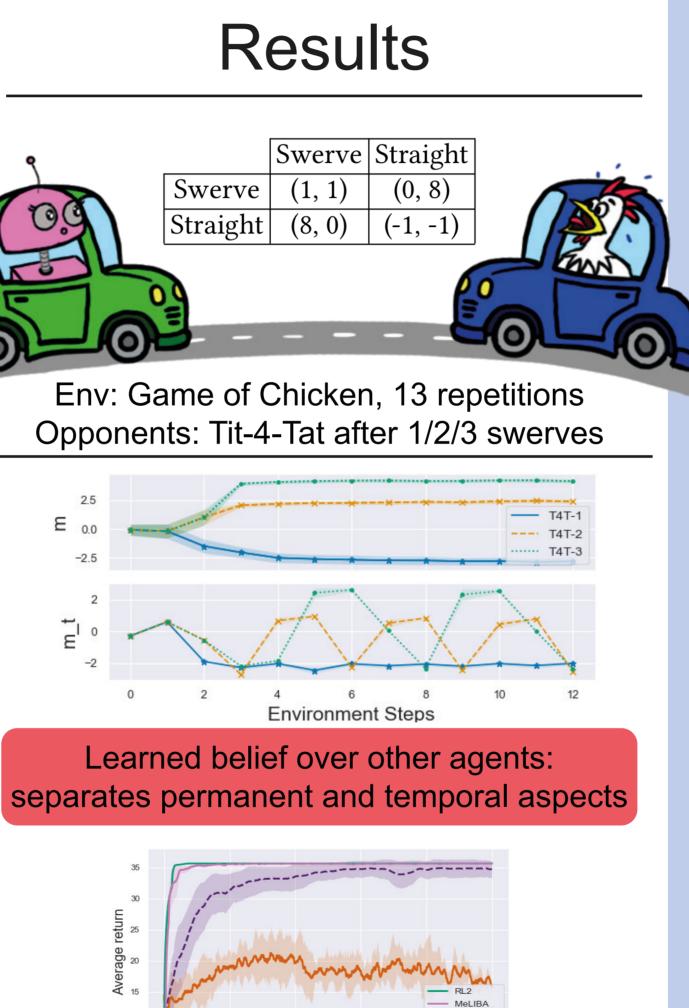
Our key contributions: MeLIBA

- Scaling IBRL to Deep Learning
- Learning *beliefs* over other agent's types (compared to e.g. [2])
- Learning beliefs of permanent and temporal aspects of other agents (compared to e.g. [3])

Future Work:

- Generate distribution of other agents (instead of hand-coding)
- Move to general POMDPs (see [3])
- Other agents that learn (during meta-training)

[1] Trong Nghia Hoang, Kian Hsiang Low. A general framework for inter- acting Bayes-optimally with self-interested agents using arbitrary parametric model and model prior. IJCAI 2013. [2] Neil Rabinowitz, Frank Perbet, Francis Song, Chiyuan Zhang, S M Ali Eslami, Matthew Botvinick. Machine Theory of Mind. ICML 2018.





MeLIBA shows good performance compared to baselines and ablations



Method: MeLIBA

Our approach for scaling IBRL:

Meta-learn how to

- (1) infer other agents' permanent & temporal types using approx. variational inference
- (2) use the approximate belief for optimal decision-making under uncertainty over the other agents' strategies.

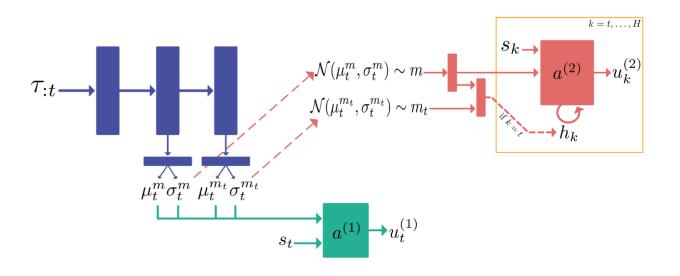
(1) Meta-learning belief inference:

Use a sequential hierarchical VAE trained to predict future actions of other agents, given current experience.

Separate latent for: permanent (m) and temporal (m t) aspect of other agent.

(2) Meta-learning the policy:

Condition policy on approximate *belief*. Trained using standard RL alongside the VAE.



^[3] Georgios Papoudakis and Stefano V Albrecht. Variational Autoencoders for Opponent Modeling in Multi-Agent Systems. AAAI Workshop on RL in Games 2020.