A new paradigm to study social and physical affordances as model-based reinforcement learning

IA pour la Robotique (IAR)
Marilyn Chahine
Zhirui Cai

What are Affordances?

- Action possibilities that the environment offers to the agent
- Properties of the environment which can only be learned through agent-environment interaction
- Affordance perception may change depending on the agent's goal
- Self-generating goals help to learn affordances

What are Affordances?

- Physical affordance:
  - Action possibilities offered by the presence of objects
  - Inferred through visual cues

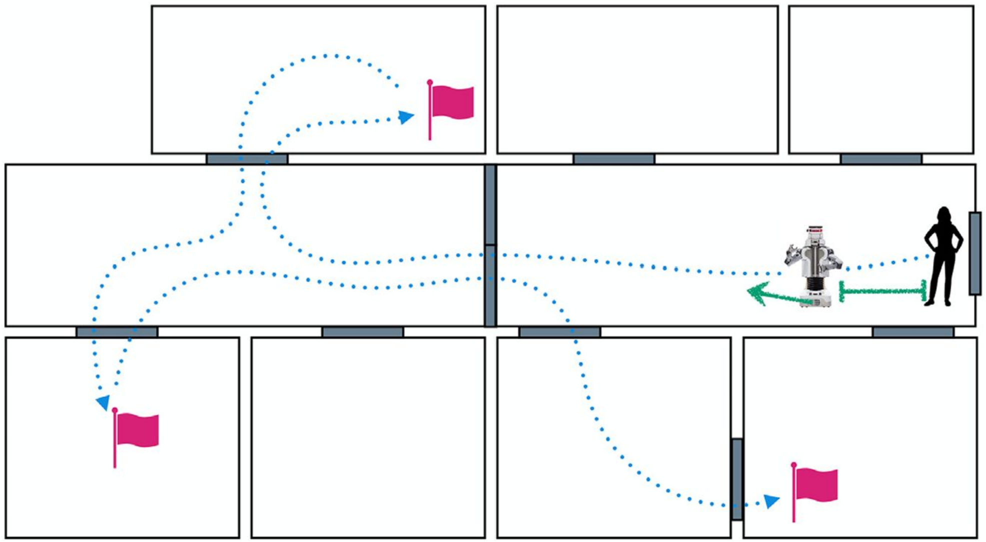
- Social affordance:
  - Action possibilities offered:
    - By another agent who can reciprocate
    - By an object whose affordance is available thanks to the presence of another agent
  - Produced effect is more uncertain than in non-social domains

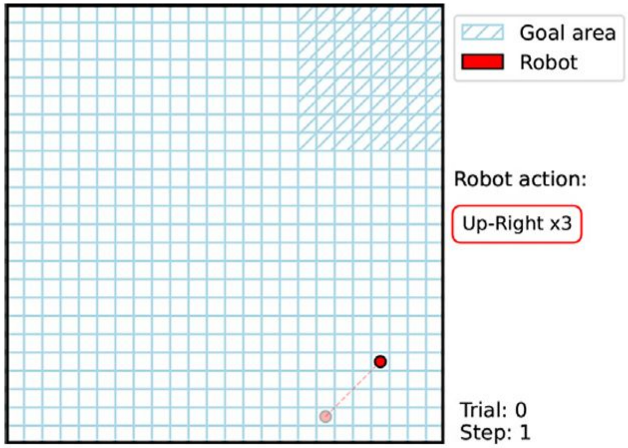
Model-Based Reinforcement Learning

- Why MBRL for this problem?
  - Learns action–effect relations
  - Fits affordances naturally
  - Adapts online to human variability
  - Handles physical + social dynamics
  - Can be combined with goal-conditioned & reward-free exploration

The Visit the Lab task

- Robot guides a human through multiple rooms
- Integrates physical & social affordances





Modelling Social Interaction

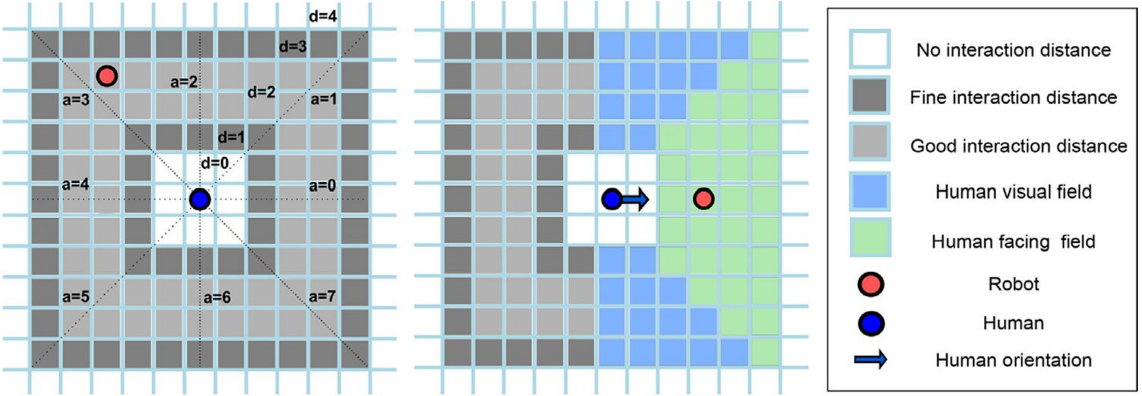
The Social Module

Inputs:

- Desired direction
- Human visual/facing field
- Relative distance & angle
- 8 interaction levels

Outputs an action out of:

- 25 navigation actions
- 5 social actions

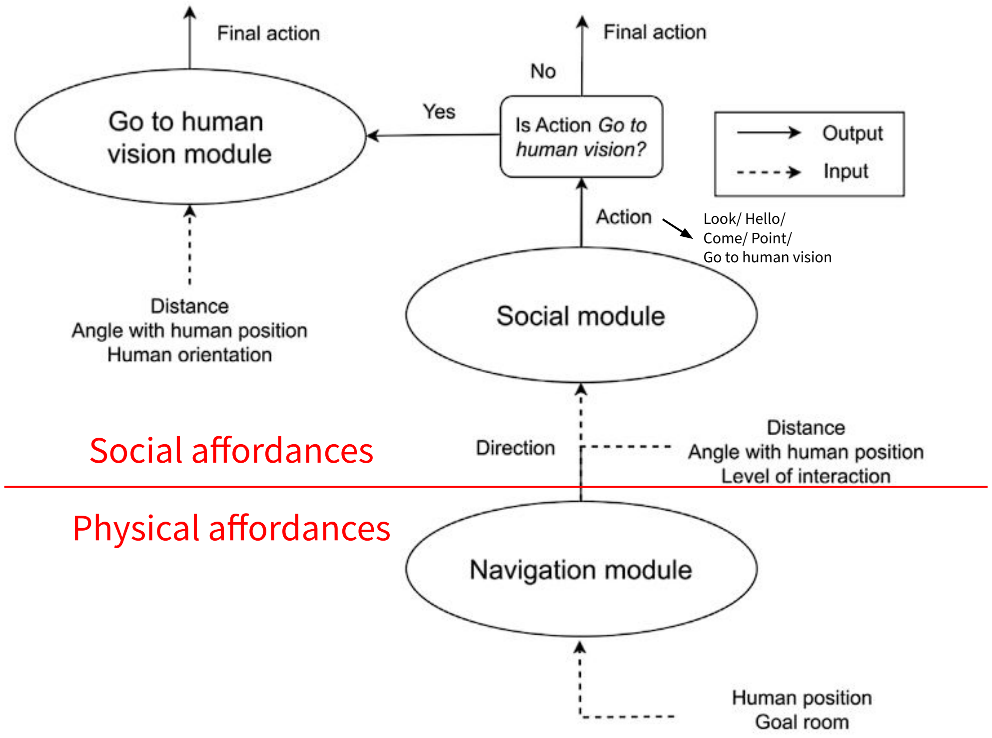


Modelling Human Behavior

Three human types:

		H1 Slow, attentive	H2 Fast, occasional attention loss	H3 Random speed, inattentive
Property	Symbol	Human 1	Human 2	Human 3
Human speeds	p_S	[1,0,0]	[0,0.5,0.5]	[0.33,0.33,0.34]
Failing hello	p_H	0	0.05	0.5
Random movement	p_M	0.1	0.05	0.2
Random eye movement	p_O	0.1	0.15	0.3
Losing Attention	p_A	0	0.05	0.1
Pointing need	p_P	0	0	0.5

Model Architecture



- Modules trained separately

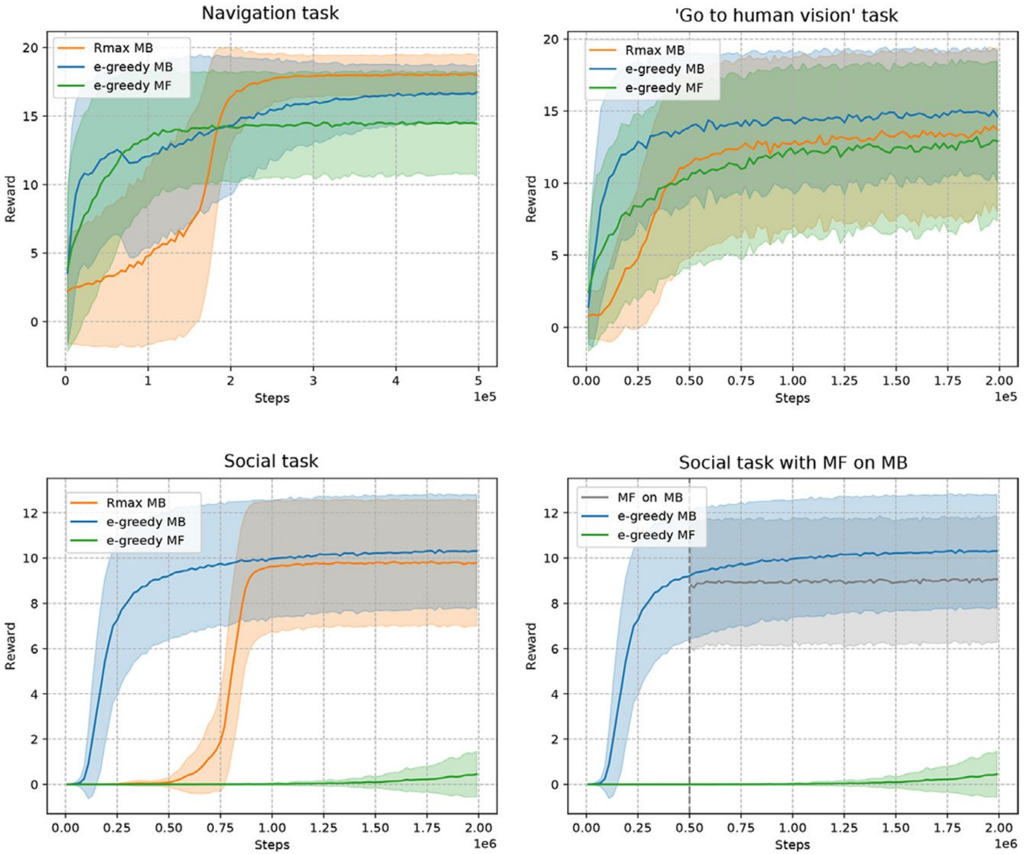
RL Algorithms used:

- Model-Free ε-greedy (Q-learning)
- Model-Based ε-greedy (value iteration)
- Model-Based greedy in the face of uncertainty (Rmax)

Results: Model-Based (MB) vs Model-Free (MF)

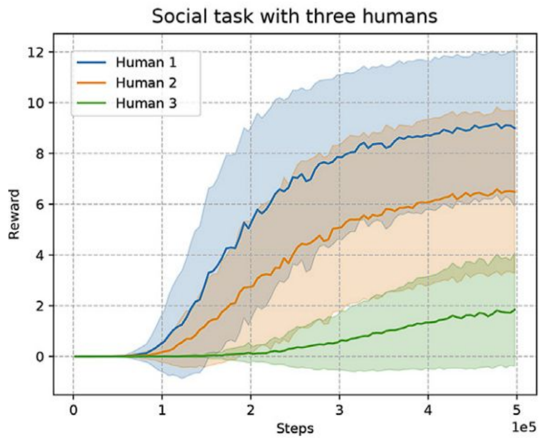
- Both MB algorithms succeed all three tasks

- MF fails the social task
- MF trained by observing MB rewards succeeds it



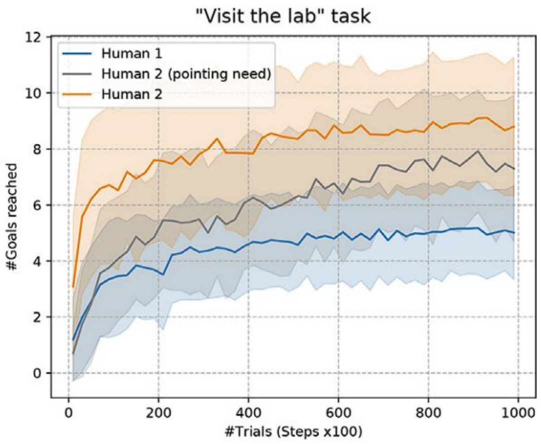
Results: Human Variability

- MB ε-greedy trained on the different types of human behaviors
  - Performance:
    - H1 > H2 > H3



Generalization:

- Can a human-specific model succeed faced with different types of behavior?
- Trained on H2
- Best adaptation when new human resembles H2
- Harder adaptation when human behavior is different



Conclusion & Future Work

Conclusions

- ➔ Importance of social affordances in robotics
- ➔ New benchmark task for combination of physical and social affordances.
- ➔ Model-based RL learns these affordances efficiently and adapts to different kinds of humans.

Future directions

- ➔ Multi-model RL with human-general/specific distinction
- ➔ Curriculum learning across modules
- ➔ Reinforcement learning agents that generate intents and options
- ➔ Theory of mind
- ➔ MF for computational cost
- ➔ Application on a robot