Knowledge Improvement and Diversity under Interaction-Driven Adaptation of Learned Ontologies

Yasser Bourahla, Manuel Atencia and Jérôme Euzenat

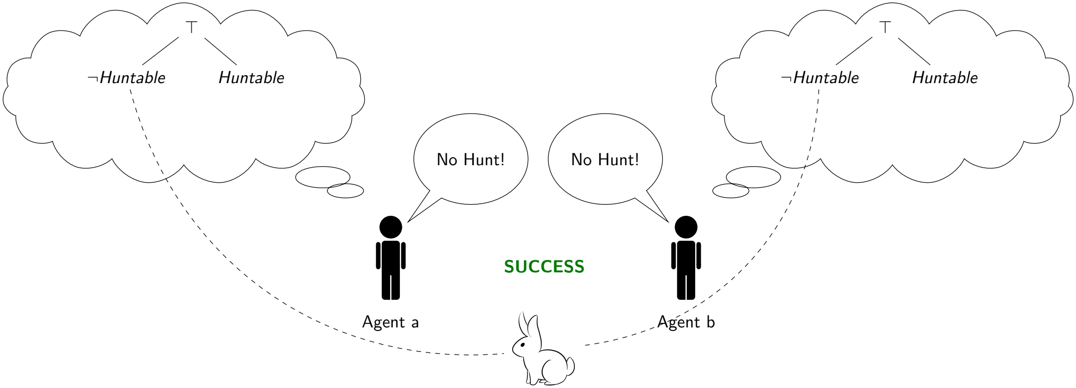
{yasser.bourahla,manuel.atencia,jerome.euzenat}@inria.fr
https://moex.inria.fr

Context

- Agents coordinate to achieve tasks in their environment.

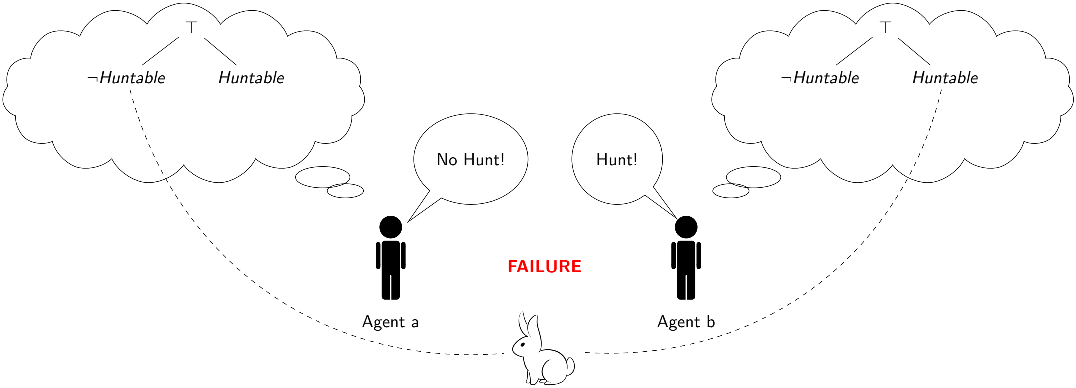
Context

- Agents coordinate to achieve tasks in their environment.
- They need to agree on their knowledge about the environment.



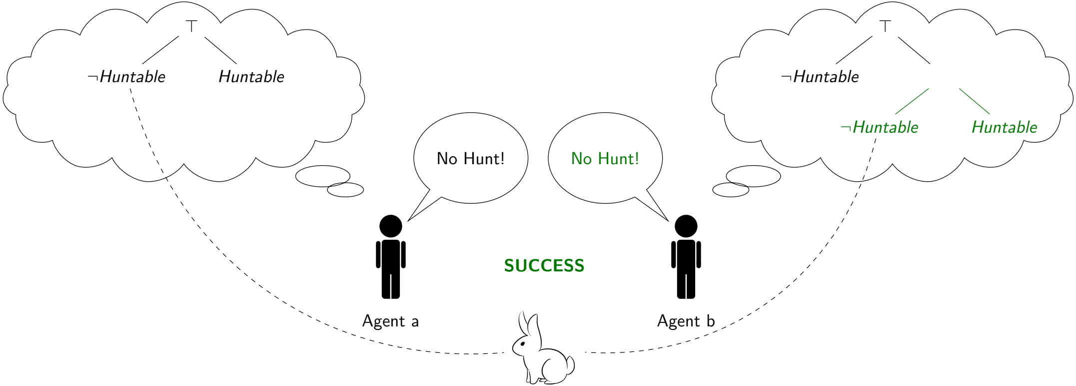
Context

- Agents coordinate to achieve tasks in their environment.
- They need to agree on their knowledge about the environment.



Context

- Agents coordinate to achieve tasks in their environment.
- They need to agree on their knowledge about the environment.



- If a disagreement happens, agents adapt their knowledge.

Problem

How is agent knowledge affected when they adapt it to agree with each other?

Problem

How is agent knowledge affected when they adapt it to agree with each other?

Q1 Can agents reach a state with successful interactions?

Problem

How is agent knowledge affected when they adapt it to agree with each other?

- Q1 Can agents reach a state with successful interactions?
- Q2 Can agents improve the accuracy of their knowledge about the environment?

Problem

How is agent knowledge affected when they adapt it to agree with each other?

- Q1 Can agents reach a state with successful interactions?
- Q2 Can agents improve the accuracy of their knowledge about the environment?
- Q3 Can agents preserve the diversity of their knowledge?

Experimental framework

Requirements:

Experimental framework

Requirements:

- Agents have knowledge about their environment.

Experimental framework

Requirements:

- Agents have knowledge about their environment.
- Agents accomplish tasks in the environment using their knowledge.

Experimental framework

Requirements:

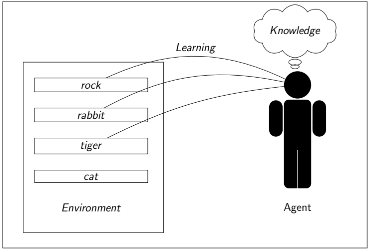
- Agents have knowledge about their environment.
- Agents accomplish tasks in the environment using their knowledge.
- Agents need to agree with each other to interact successfully.

Experimental framework

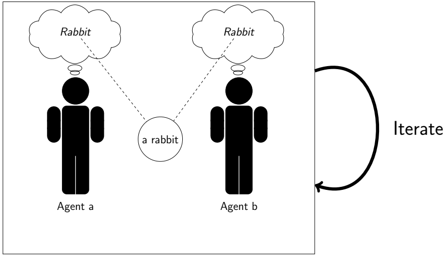
Requirements:

- Agents have knowledge about their environment.
- Agents accomplish tasks in the environment using their knowledge.
- Agents need to agree with each other to interact successfully.

Process:



Learning



Adaptation

Agent learning

rock
$\{\neg mobile, \neg fangs, \neg eyes\}$

rabbit
$\{mobile, \neg fangs, eyes\}$

tiger
$\{mobile, fangs, eyes\}$

cat
$\{mobile, fangs, eyes\}$

...

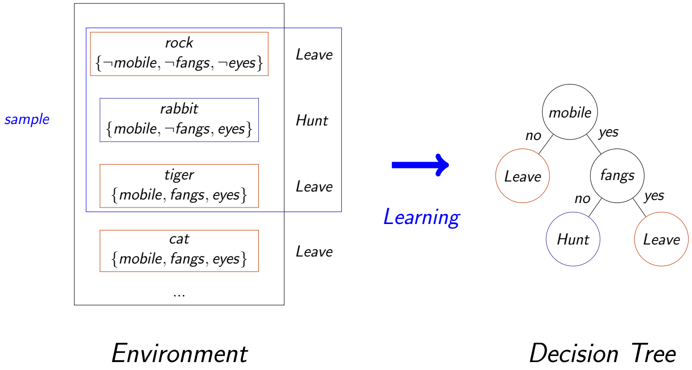
Environment

Agent learning

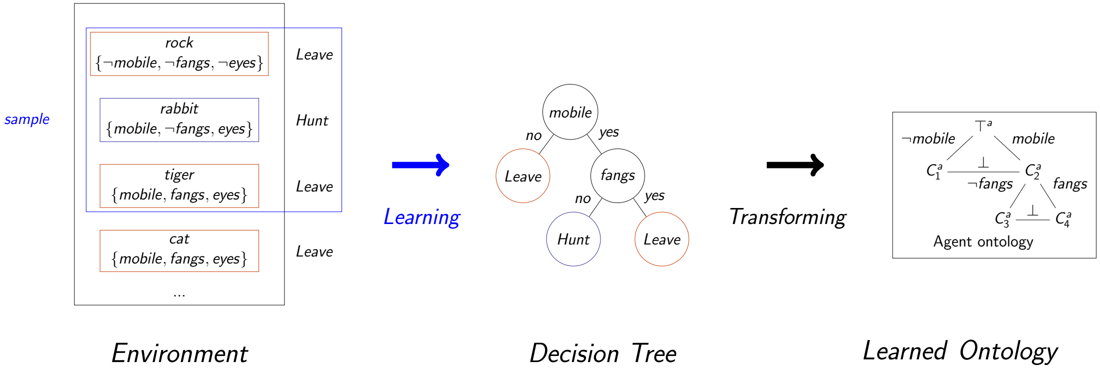
rock $\{\neg mobile, \neg fangs, \neg eyes\}$	*Leave*
rabbit $\{mobile, \neg fangs, eyes\}$	*Hunt*
tiger $\{mobile, fangs, eyes\}$	*Leave*
cat $\{mobile, fangs, eyes\}$	*Leave*
...	

Environment

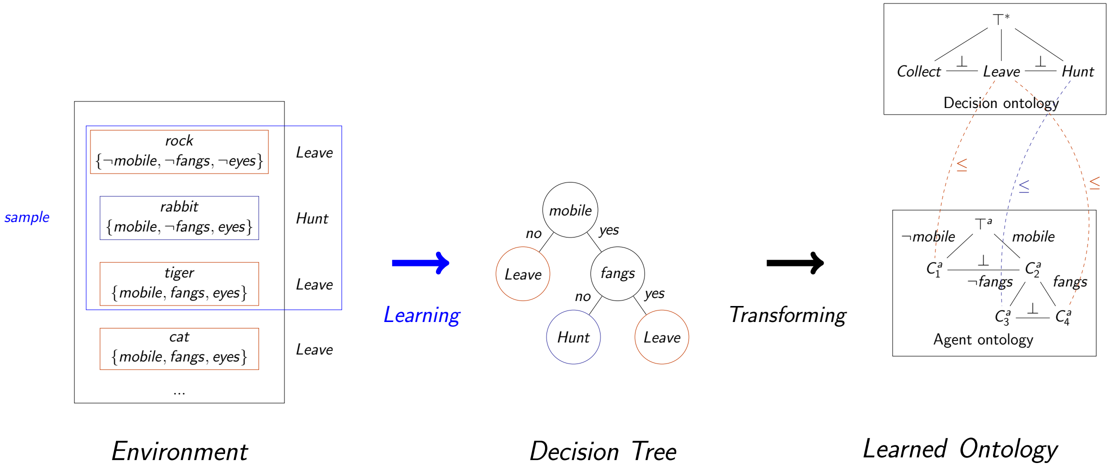
Agent learning



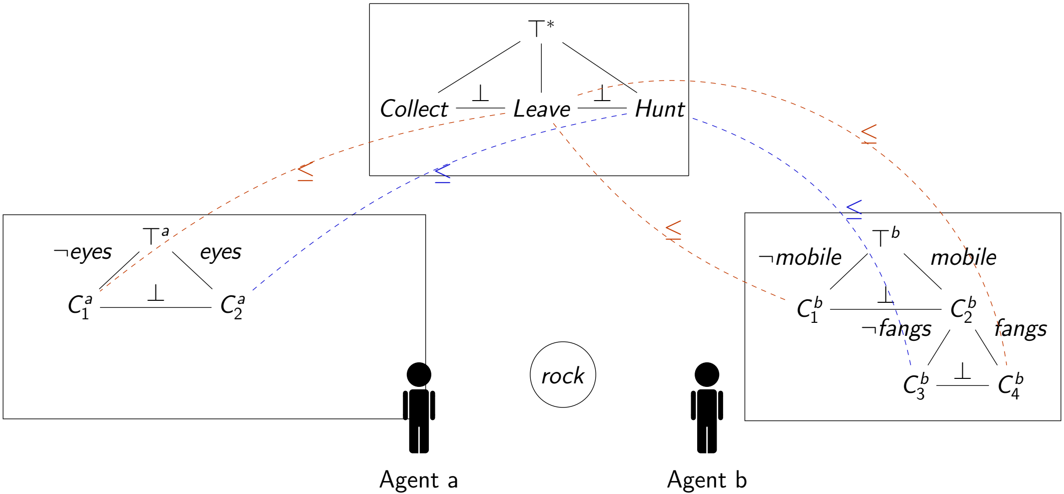
Agent learning



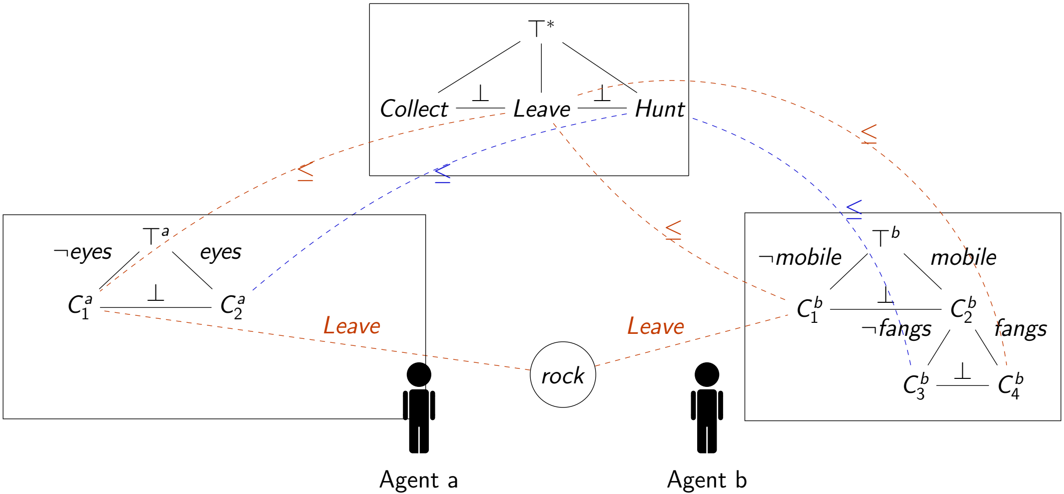
Agent learning



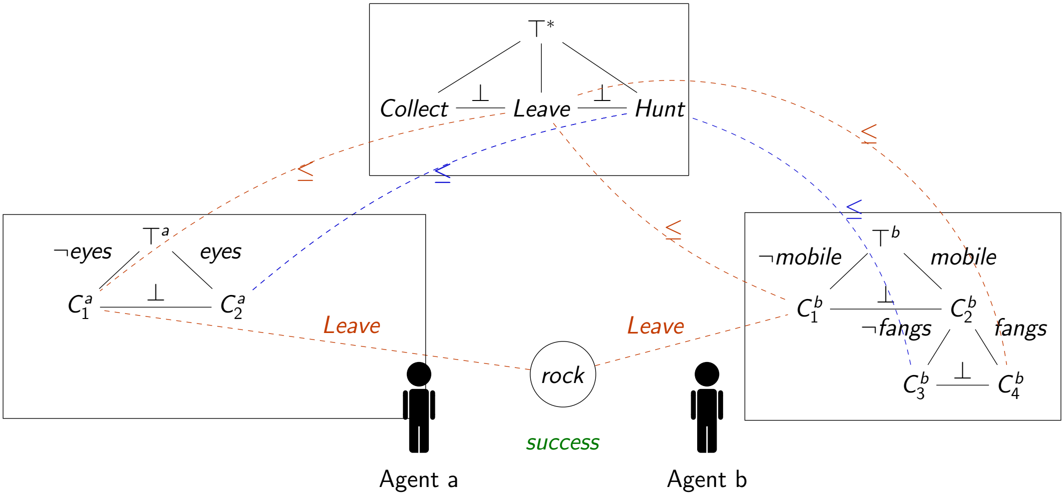
Agent-to-agent interaction



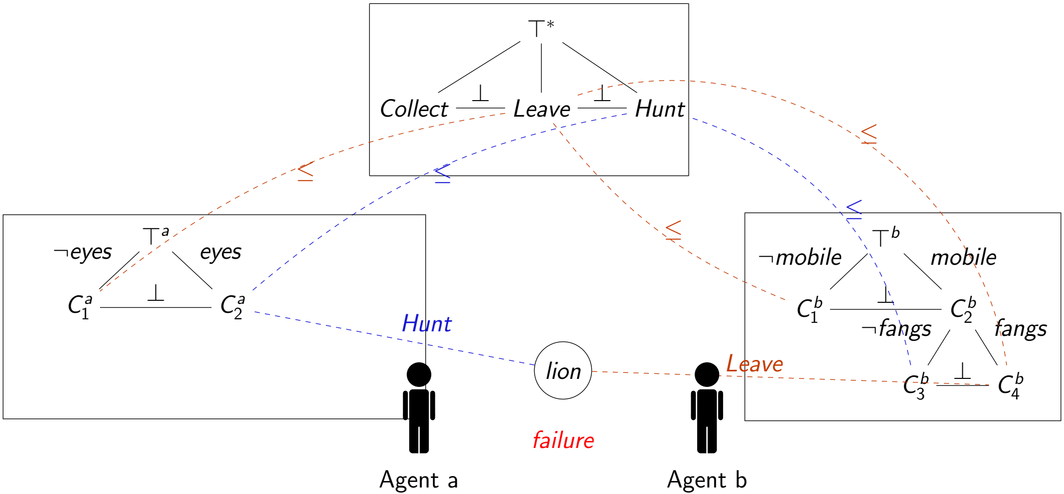
Agent-to-agent interaction



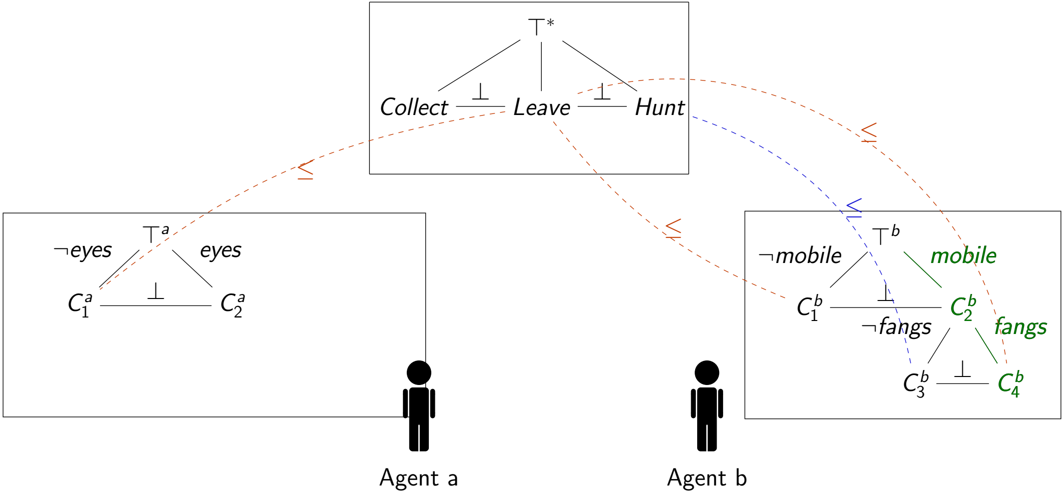
Agent-to-agent interaction



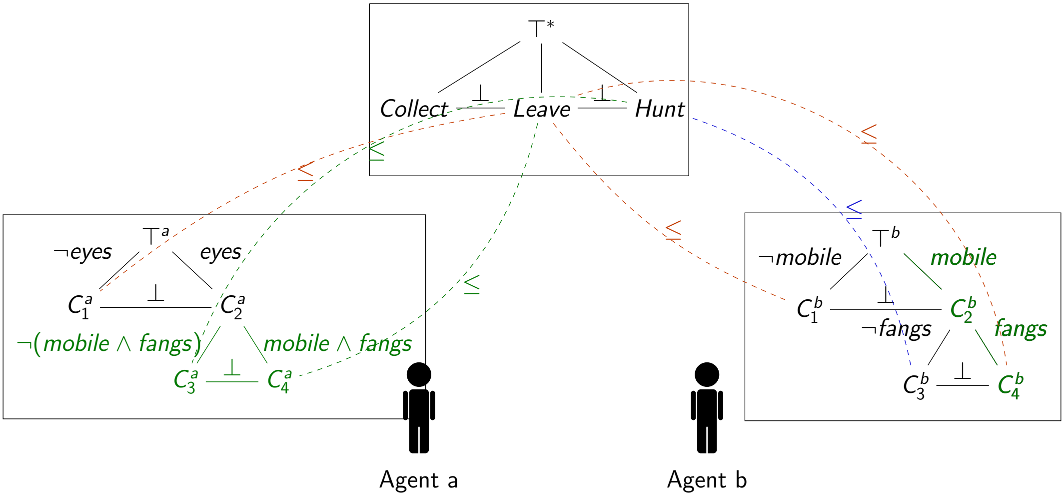
Agent-to-agent interaction



Agent-to-agent interaction



Agent-to-agent interaction



Hypotheses

H1 Agent interactions become successful.

Hypotheses

H1 Agent interactions become successful.

H2 Agent knowledge about the environment will becomes more accurate.

Hypotheses

- H1 Agent interactions become successful.
- H2 Agent knowledge about the environment will becomes more accurate.
- H3 Agents do not necessarily converge to the same ontologies.

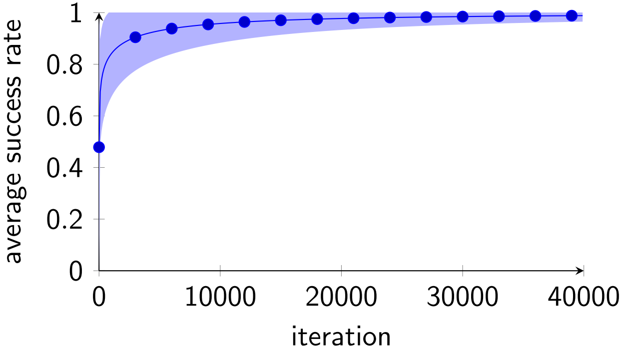
Experiment plan

For each variation of parameters, the experiment is run 10 times.

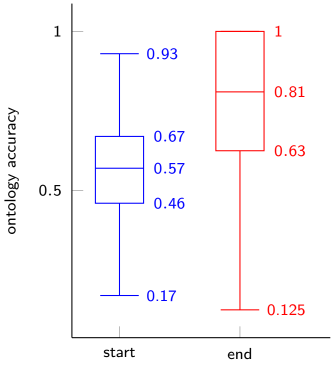
Parameter	Range
Number of agents	$\{2, 5, 10, 20, 40\}$
Number of features	$\{3, 4, 5\}$
Number of decision classes	$\{2, 3, 4\}$
Task ratio	$\{0.2, 0.4, 0.6, 0.8\}$
Training ratio	$\{0.1, 0.3, 0.5\}$
Number of iterations	40000

Results: Success rate

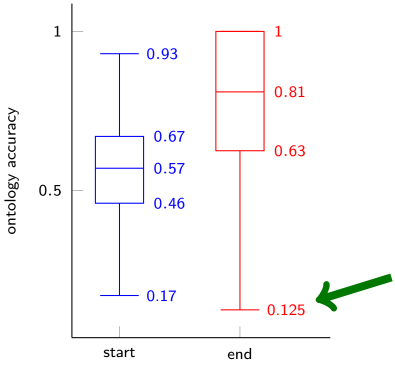
The success rate converges to 1. Hypothesis 1 **accepted**.



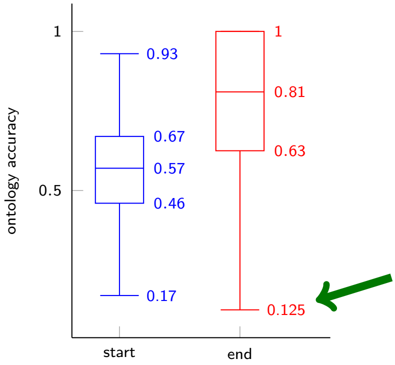
Results: Accuracy



Results: Accuracy

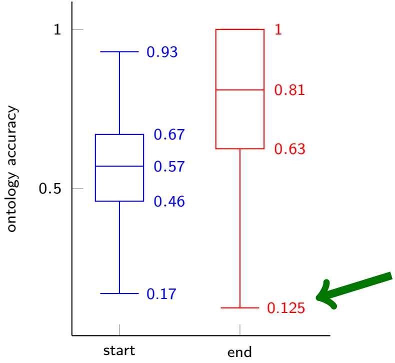


Results: Accuracy



- H2 weak version: Agent knowledge accuracy improves **in average** (**accepted**)

Results: Accuracy



- H2 weak version: Agent knowledge accuracy improves **in average** (**accepted**)
- H2 strong version: Agent knowledge accuracy improves **for all runs** (**rejected**)

Results: Accuracy

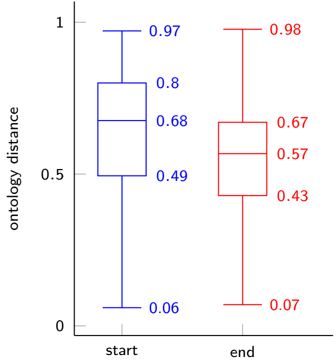
The accuracy drops in **3.5%** of the runs.

Agents	2	5	10	20	40	total
runs	141	44	4	0	0	189
percentage	2.43	0.75	0.05	0	0	3.23

Table: Number of runs with negative accuracy difference by number of agents and task ratio (each cell = 1440 runs).

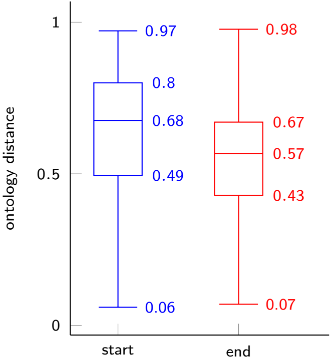
Results: Ontology distance

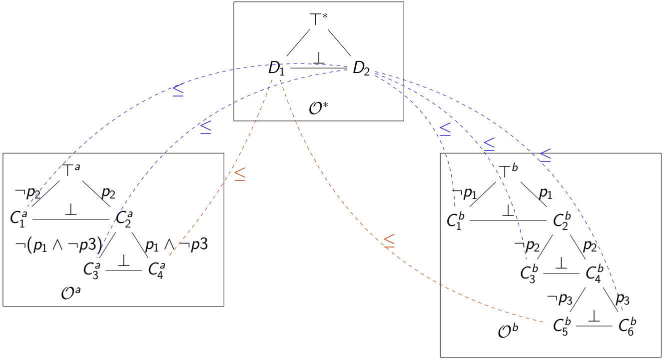
Agents maintain different ontologies in 90.78% of the runs.



Results: Ontology distance

Agents maintain different ontologies in 90.78% of the runs. Hypothesis 3 **accepted**.





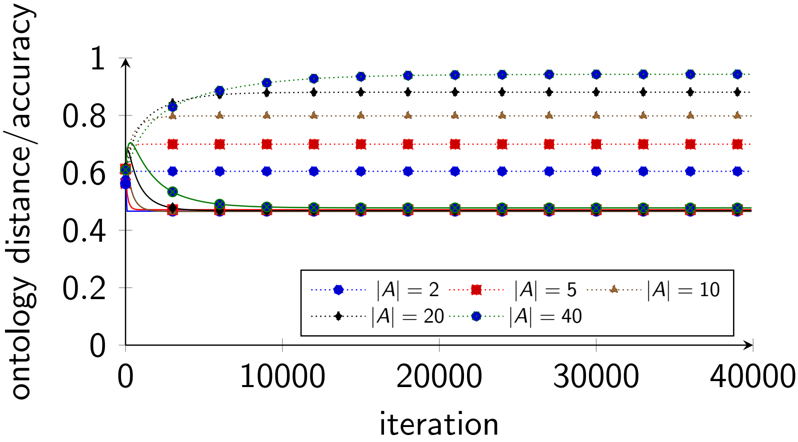
Results: Factor effects

ANOVA test results.

Factor	Success rate	Distance	Accuracy
Number of agents	$\ll 0.01$	0.475	$\ll 0.01$
Number of features	$\ll 0.01$	$\ll 0.01$	0.40
Number of decision classes	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$
Task ratio	$\ll 0.01$	< 0.01	$\ll 0.01$
Training ratio	$\ll 0.01$	$\ll 0.01$	$\ll 0.01$

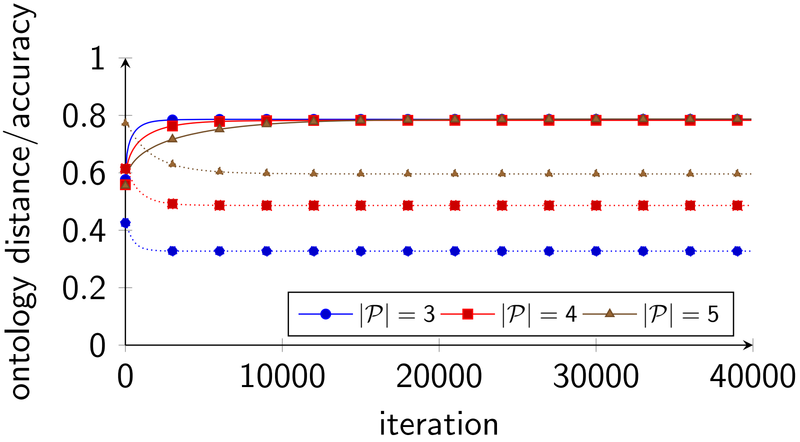
Results: Factor effects

Effect of number of agents on accuracy.



Results: Factor effects

Effect of number of features on ontology distance.



Comparison with AMAIL on real data

Experiment repeated by generating the environment from the Zoology dataset.

Ontañón, Santiago and Plaza, Enric (2015)
Coordinated Inductive Learning Using Argumentation-Based Communication
Autonomous Agents and Multi-Agent Systems 29, 2, 266 – 304.

Comparison with AMAIL on real data

Experiment repeated by generating the environment from the Zoology dataset.

- The environment objects and their decisions are generated from the dataset instead of randomly with a random number of features.

Ontañón, Santiago and Plaza, Enric (2015)
Coordinated Inductive Learning Using Argumentation-Based Communication
Autonomous Agents and Multi-Agent Systems 29, 2, 266 – 304.

Comparison with AMAIL on real data

Experiment repeated by generating the environment from the Zoology dataset.

- The environment objects and their decisions are generated from the dataset instead of randomly with a random number of features.
- The task ratio and training ratio are fixed to 0.2.

Ontañón, Santiago and Plaza, Enric (2015)
Coordinated Inductive Learning Using Argumentation-Based Communication
Autonomous Agents and Multi-Agent Systems 29, 2, 266 – 304.

Comparison with AMAIL on real data

Method	$\|A\|$	Precision	F-measure	Recall	Accuracy
Simulation	2	0.88	0.87	0.86	0.951
	5	0.91	0.89	0.88	0.964
	10	0.94	0.92	0.91	0.977
	20	0.96	**0.94**	**0.93**	**0.984**
	40	0.95	**0.94**	**0.93**	0.983
A-MAIL	2	0.97	0.85	0.75	0.950
	3	**0.98**	0.89	0.81	0.968
	4	0.97	0.90	0.84	0.966
	5	**0.98**	0.93	0.88	0.980

Conclusion

We designed an experimental framework and used it to show that:

Conclusion

We designed an experimental framework and used it to show that:

- Agents can reach a state of successful interactions by adapting their knowledge to agree with each other.

Conclusion

We designed an experimental framework and used it to show that:

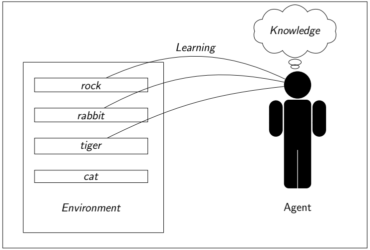
- Agents can reach a state of successful interactions by adapting their knowledge to agree with each other.
- Agents can improve the accuracy of their knowledge.

Conclusion

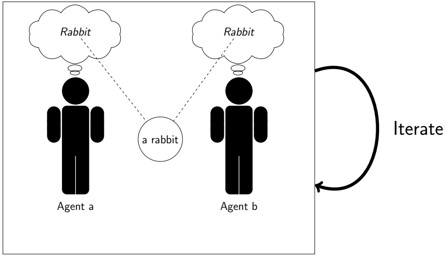
We designed an experimental framework and used it to show that:

- Agents can reach a state of successful interactions by adapting their knowledge to agree with each other.
- Agents can improve the accuracy of their knowledge.
- Agents maintain the diversity of their knowledge.

Conclusion

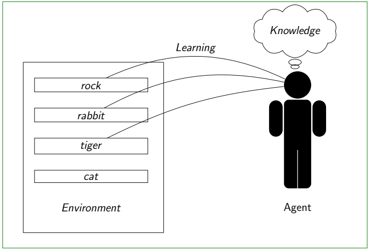


Learning

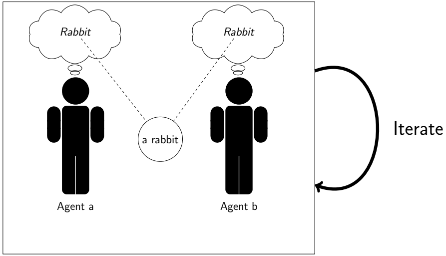


Adaptation

Conclusion

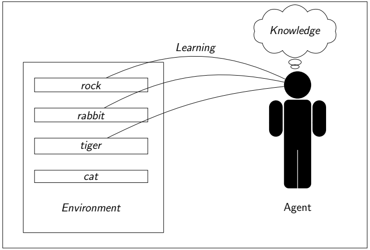


Learning

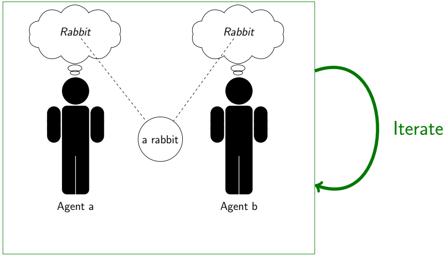


Adaptation

Conclusion

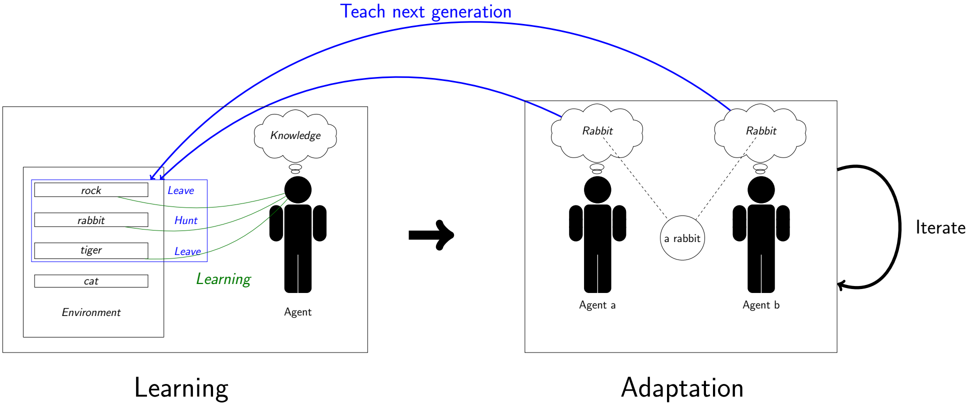


Learning



Adaptation

Conclusion


Teach next generation
rock
rabbit
tiger
cat
Environment
Leave
Hunt
Leave
Learning
Knowledge
Agent
Rabbit
Rabbit
a rabbit
Agent a
Agent b
Iterate
Learning
Adaptation

Thank you!