Knowledge evolution:
a computational cultural knowledge evolution perspective

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Knowledge evolution

Modalities of knowledge evolution:

- explicit / implicit;
- automatic / manual;
- invividual / social;
- continuous / discrete.

	explicit	automatic	individual	continuous
Belief revision	√	√	√	-
Neural network	-	√	√	√
Knowledge engineering (EGC)	√	-	√	-
Knowledge management	-	-	-/√	√

Potential application domains

In an environment where humans and machines cooperate, both should be able to adapt and evolve their knowledge.

- Long-term knowledge evolution (semantic web evolution, science);
- Social robotic (across robots and human beings).

  Sample setting:
  - Set of robot carer for elderly people
  - Entertaining them, helping following prescriptions, etc.
  - Have to interact among themselves and with patients, medical staff and relative
  - Ever evolving context (turn-over, condition evolution, etc.)

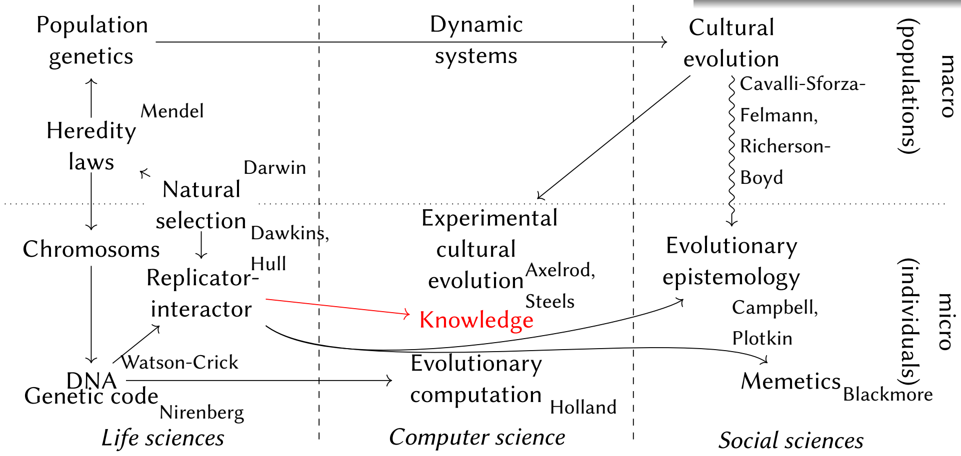
Evolution theory

Evolution is a control mechanism based on three principles:

- Variation
- Transmission (inheritance)
- Selection

It can be applied to a variety of objects.

Evolution of evolution



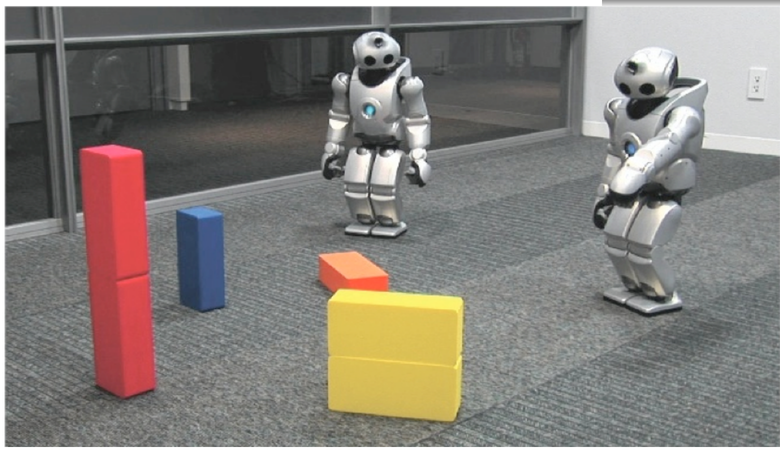
Experimental cultural evolution

- Cultural evolution comes from anthropology
- Experimental cultural evolution applies multi-agent simulation to cultural artifacts:
  - Axelrod 1997 Culture propagation
  - Reynolds 1994 Cultural algorithms
  - Oudeyer 1997 Autoorganisation of vocalisation
  - Wang-Gasser 2002 Ontology alignment
  - Kirby 2008 Language transmission
  - Steels 2012 Cultural language evolution
- Offers a systematic experimentation framework in which agents play "games"

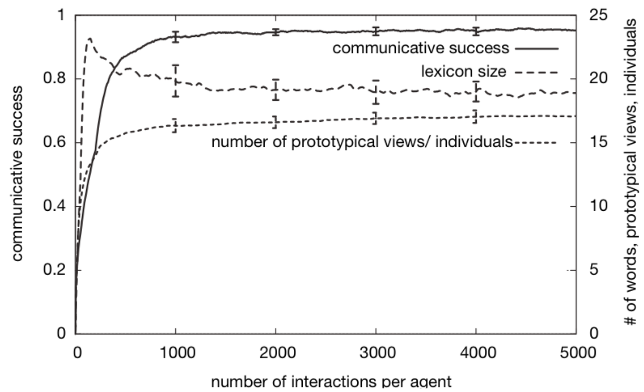
Rules of the situated naming game [Steels 2012]

1. A robot tells the name of an (randomly chosen) object (if it has no name a new one is created)
2. The other robot must identify the object and designate the object
3. The first robot perceives what is shown and nods if it corresponds to his name (SUCCESS)
4. Otherwise (FAILURE), he points at the actual object
5. The second robot records the outcome of the game

Steels movie

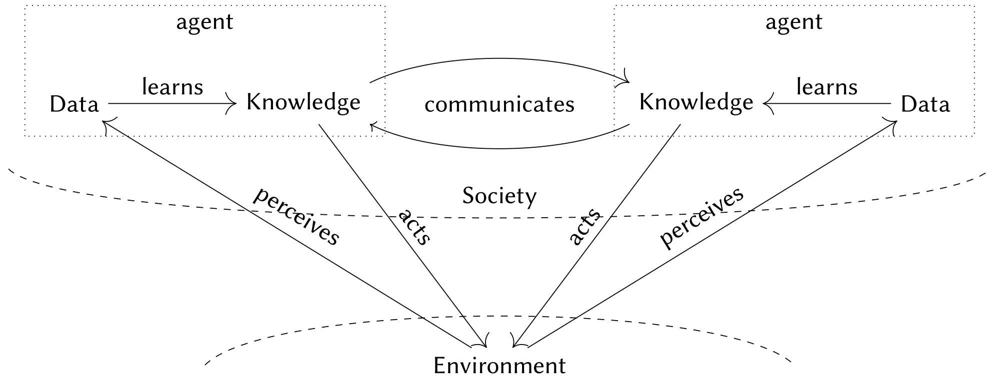


Results [Steels 2012]



- Robots converge towards common names for objects in the environments.
- They converge faster if they can exchange their lexicons.

Knowledge communication and evolution



Goal

Study the principles of knowledge evolution in a controlled setting.

- Understanding mechanisms by which knowledge evolves
- …in a society of people and AI systems
- How cooperating impacts knowledge (and learning)

Can be used for:

- Understanding human behaviour
- Developing artificial agents
- ... and of course, they may interact.

Methods

Combining

Knowledge representation

and

experimental cultural evolution

- experimentally, through multi-agent simulation, and
- theoretically, through logical modelling.

Basics of experimental cultural knowledge evolution

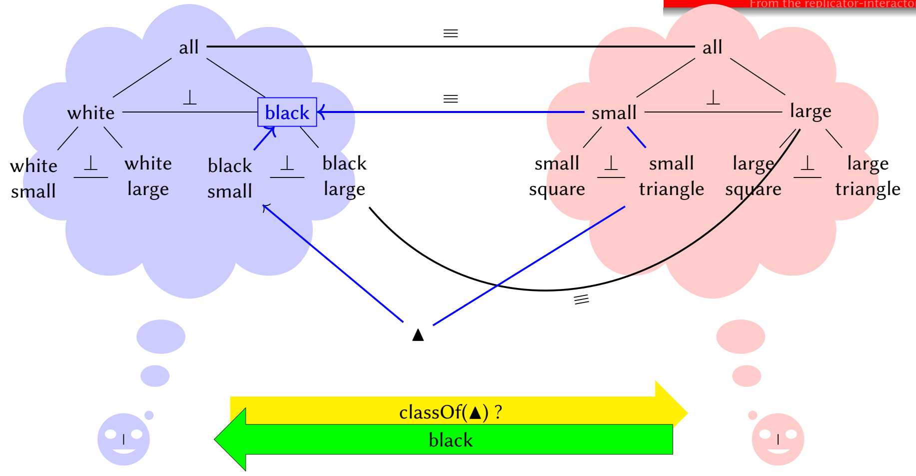
- Populations of agents bearing knowledge;
- Using it for interacting with each others and their environment (games);
- Locally adapting their knowledge at the issue of each interaction.

- Random simulations of a large number of games;
- Check that agents have indeed improved at playing the game (success rate);
- Observe global properties of the resulting knowledge and of its evolution.

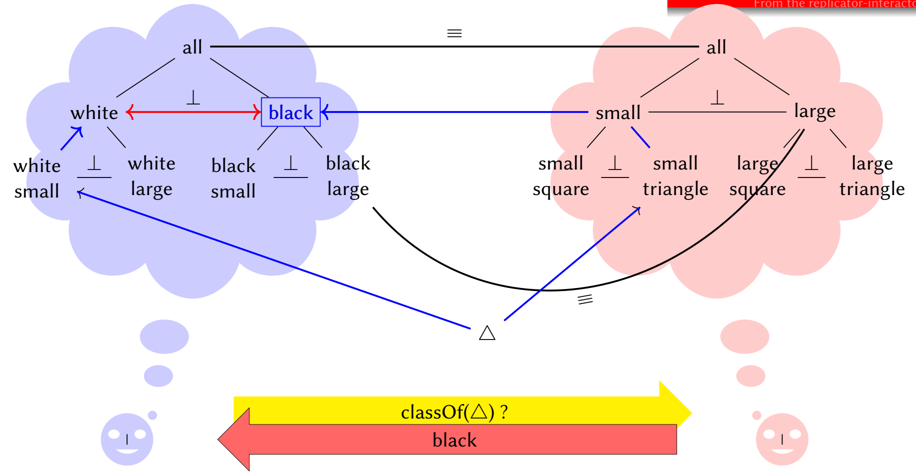
Cultural alignment repair

- Take alignments as culture (not necessarily ontologies):
- Have agents trying to communicate using available alignments;
- Let them repair them on the fly.

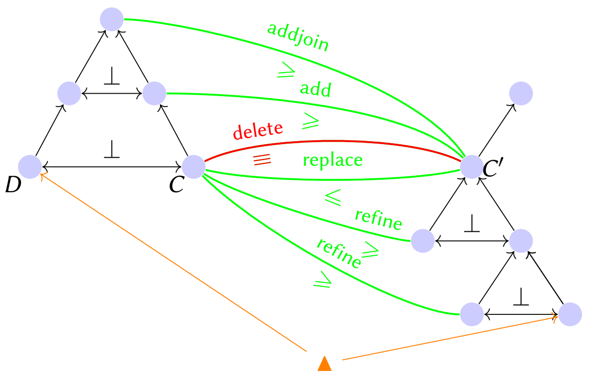
Alignment repair game



Alignment repair game



Adaptation operators



Properties of operators

These operators share two particular properties:

Safeness after applying the operator, if the same instance is chosen, the problem would not occur again (maybe a different problem would occur);

Entailment each correspondence added by any of the operators was entailed by the removed correspondence.

Such properties are sanctioned by the semantics of ontologies and alignments.

Experimental conditions

A population of [4] agents are given ontologies using a permutation of the features of the environment.

Randomly selected agents play a specific number of games [10000].

Various measures [averaged on 10 run] are recorded:

Success rate : the ratio of success over games played.

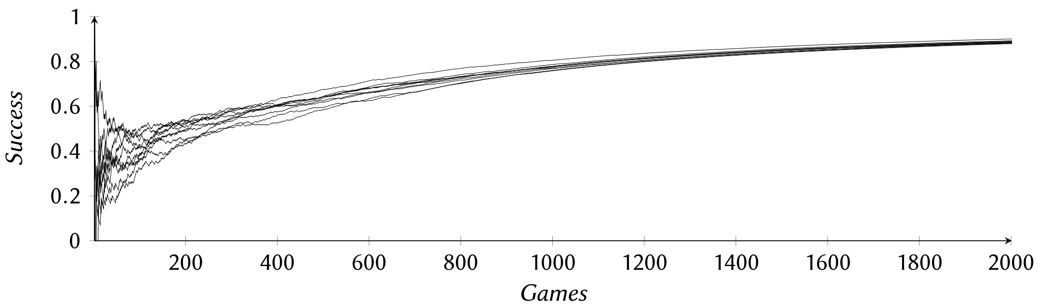
Semantic precision and recall : degree of correctness and completeness of the resulting alignments (F-measure averaging them).

Incoherence rate : proportion of incoherent correspondences in alignments.

Experimental questions and results

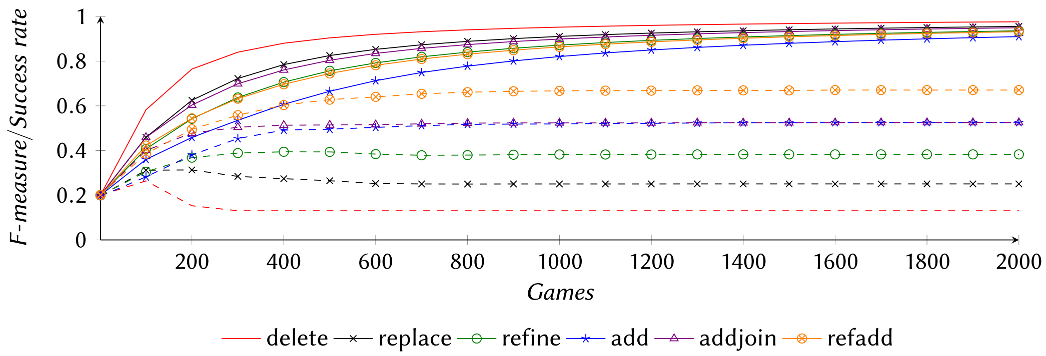
1. Does the process converge?
   → Asymptotically to 100% success rate
2. What is the effect of adaptation operators?
   → Various operators and modalities to increase precision, recall and coherence.
3. How do they compare to baselines?
   → Clearly better; The larger the network, the better
4. Does it scale?
   → Not really, but that's not the point
5. Can it be improved?
   → Yes in various, automatic [IJCAI 2017] and adaptive, ways.
6. Can it start from scratch?
   → Yes [PRIMA 2017].
7. Can this extend to ontology adaptation?
   → Yes [AAMAS 2021].

Convergence and operators



[20140306-NOOR] operator=add; #agents=4; #games=2000; #runs=1

Success rate and F-measure



[20180308-NOOR] operator=del,repl,add,addjoin,refine,refadd; #agents=4; #games=2000; #runs=10

Initial results

Operator	Size	Success rate	Inc. degree	Sem. Precision	Sem. F-measure	Sem. Recall	Max Conv.
reference	86	1.0	0.0	1.0	1.0	1.0	1
initial	54	0.24	0.34	0.11	0.20	0.89	-
delete	6	1.00	0.00	1.00	0.13	0.07	290
replace	12	0.99	0.02	0.96	0.25	0.14	1224
refine	20	0.99	0.03	0.95	0.38	0.24	1224
add	31	0.98	0.16	0.79	0.52	0.39	1526
addjoin	31	0.99	0.16	0.79	0.52	0.39	1526
refadd	48	0.99	0.15	0.79	0.67	0.58	1554
Alcomo	28	0.43	0.0	0.21	0.26	0.33	-
LogMap	29	0.51	0.0	0.24	0.26	0.29	-

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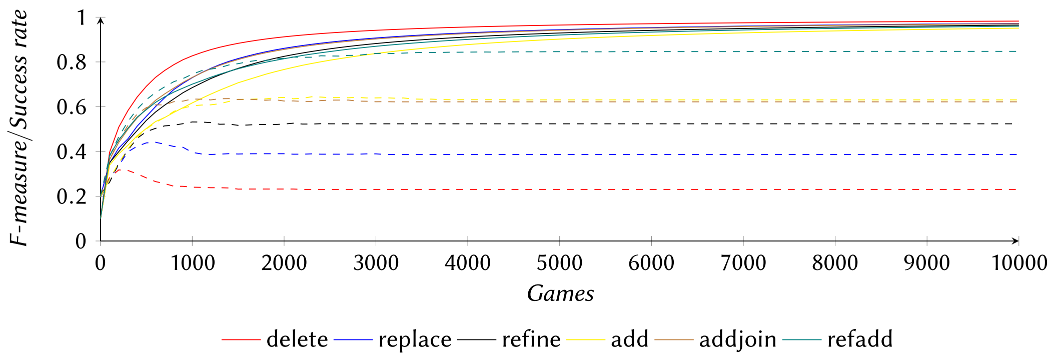
Results with expansion and relaxation [IJCAI 2017]

Operator	Size	Success rate	Inc. degree	Sem. Precision	Sem. F-measure	Sem. Recall	Max Conv.
delete	13	0.98	0.00	1.00	0.23	0.13	2116
replace	25	0.97	0.00	1.00	0.39	0.24	3038
refine	34	0.96	0.00	1.00	0.52	0.35	2450
add	47	0.95	0.00	1.00	0.63	0.46	4578
addjoin	46	0.97	0.00	1.00	0.62	0.45	3191
refadd	70	0.96	0.00	1.00	0.85	0.73	8114
w.r.t. initial	+		−	+	+	+	+

[20180530-NOOR] operator=del,repl,add,addjoin,refine,refadd; expand=mem; im=80%; #agents=4; #games=10000; #runs=10

Relaxation+expansion success rate and F-measure [IJCAI 2017]



[20180530-NOOR] operator=del,repl,add,addjoin,refine,refadd; expand=mem; im=80; #agents=4;

Further exploration

1. Altering ontologies [see Yasser]
2. Learning ontologies and alignments [see Yasser]
3. Maintaining several representations
4. Performing several tasks
5. Involving several populations and heterogeneous agents
6. Involving differential reproduction
7. Using different selective pressure and lethal decisions
8. Adding curiosity to agents
9. Selecting the adaptation operators
10. Modifying the environment
11. …

Dynamic Epistemic Ontology Logic (DEOL): Syntax

The *syntax*, $\mathcal{L}_{DEOL}$, of (multi-agent) DEOL is defined by:

$$\phi ::= C(o) \mid C \sqsubseteq D \mid C \sqsupseteq D \mid C \oplus D$$
$$\mid \phi \wedge \psi \mid \neg\phi$$
$$\mid K_a\phi \mid B_a\phi \qquad a \in \mathcal{A}$$
$$\mid [!\phi]\psi \mid [\uparrow\phi]\psi$$

DEOL: Semantics

Plausibility-based dynamic epistemic logic (Kripke models with plausibility relation)

Knowledge and beliefs are determined according to the plausibility relation, which acts as accessibility relation (when comparable):

Knowledge What is true in all plausible worlds;
Belief What is true in the most plausible accessible worlds.

Ontological and alignment statements are interpreted in set-theoretic way as in description logics.

Dynamic modalities acts as model selectors:

Announcement $!\phi$
Only worlds satisfying ϕ are preserved;

Conservative upgrade $\uparrow\phi$
The best worlds with respect to plausibility satisfying ϕ become more plausible than all.

Alignment repair game in DEOL

τ: Ontologies are knowledge ($K_a(C \sqsubseteq D)$); alignments are beliefs ($B_a(C \sqsubseteq C')$ and ($B_b(C \sqsubseteq C')$).

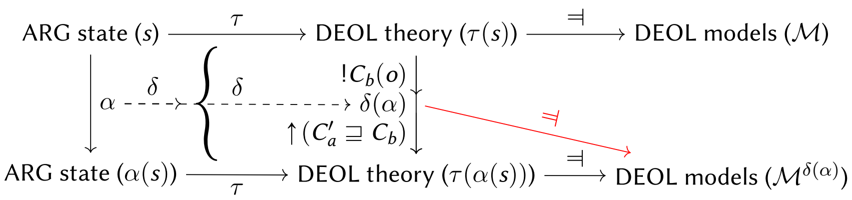
Faithfulness:

$$\forall\phi, \mathcal{O}_a \models \phi \Rightarrow \tau(s) \models K_a\phi$$
$$\text{(if } s \text{ locally consistent) } \tau(s) \models K_a\phi \Rightarrow \mathcal{O}_a \models \phi$$
$$\forall\gamma, A_{a,b} \models_a \gamma \Rightarrow \tau(s) \models B_a\gamma$$

Outcome of a game expressed by:

- Announcement of faulty instance, e.g. $!small_b(\triangle)$
- Repair action, e.g. for add, $\uparrow(\neg(largeblack_a \sqsupseteq small_b) \wedge black_a \sqsupseteq small_b))$

Translation

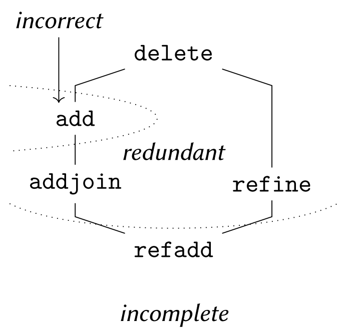


Properties of operators (α):

- correctness: $\forall s, (\tau(s))^{\delta(\alpha)} \models \tau(\alpha(s))$
- completeness: $\forall s, \tau(\alpha(s)) \models (\tau(s))^{\delta(\alpha)}$
- redundancy: $\forall s, (\tau(s))^{!C_b(o)} \models \tau(\alpha(s))$

Results [AAMAS2020]

- fair logical model of the game;
- exhibits properties of operators:
  - all operators, but add, are correct;
  - all operators are incomplete;
  - all operators, but refadd, are (unilaterally) partially redundant.



Discussion and perspectives

Issues:

- local reasoning vs. global reasoning;
- adaptive agents forget facts, not logical agents;
- public signature awareness [LAMAS 2020];

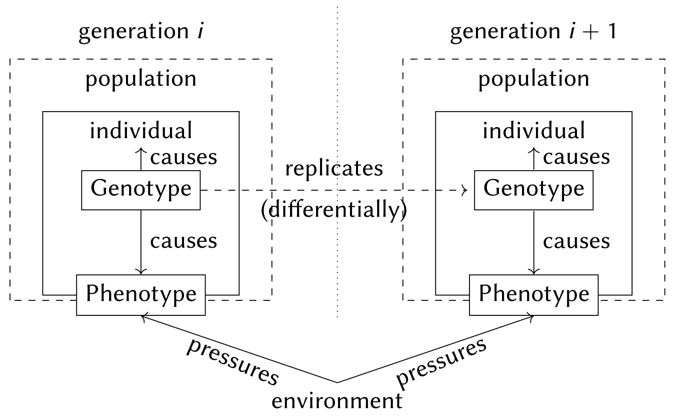
This is the result of a trade-off between adaptive and logical agents

- We could make the logic closer to the adaptive agents;
- or implement logical agents

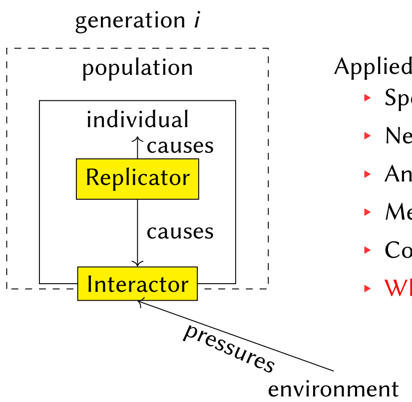
At least, it is not obvious to model these concepts with logics.

This suggests that it would be even more interesting to try to model cultural knowledge evolution with dynamic epistemic logic + belief revision.

The replicator-interactor framework



The replicator-interactor framework



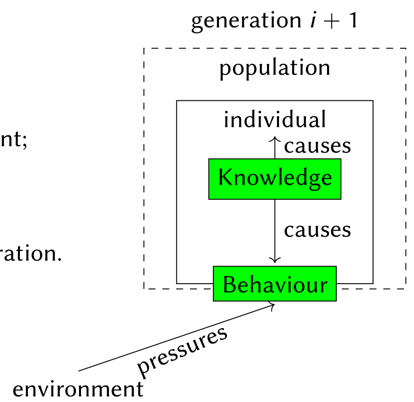
Applied to:

- Species,
- Neurons,
- Antibodies,
- Memes,
- Company structures,
- What about cultural knowledge evolution?

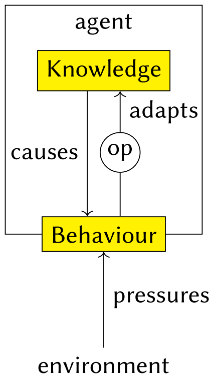
The replicator-interactor framework

Issues:

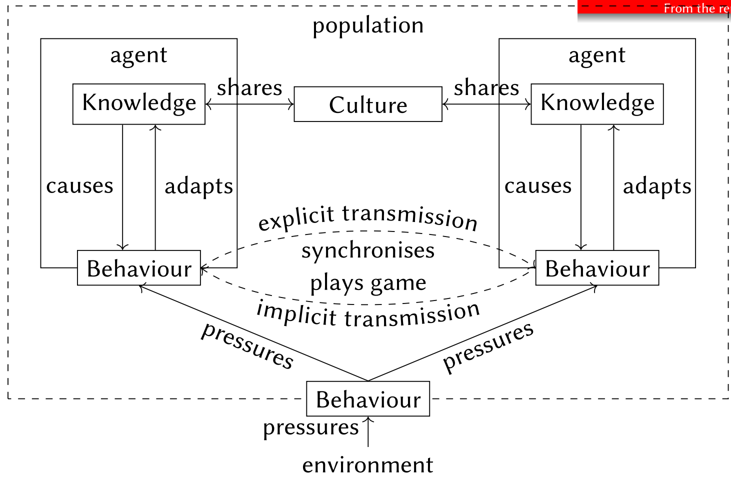
- Knowledge does not create the agent;
- The agent controls its knowledge;
- There is no population;
- There is no reproduction, nor generation.



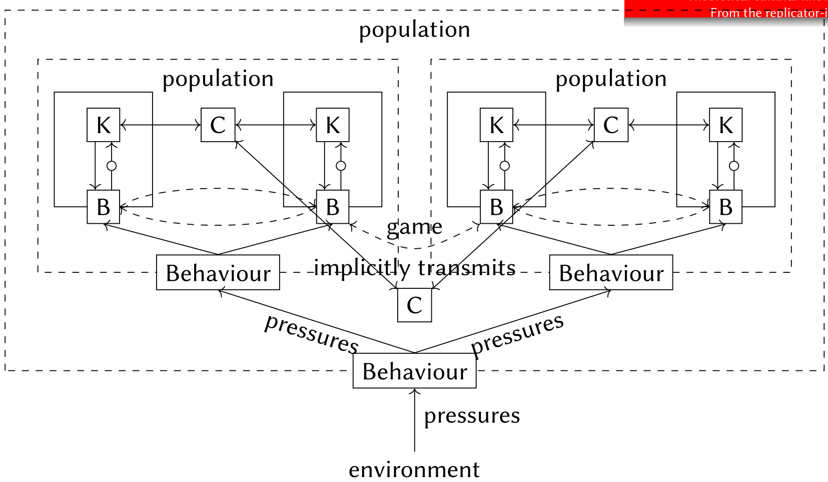
Knowledge as replicator/behaviour as interactor



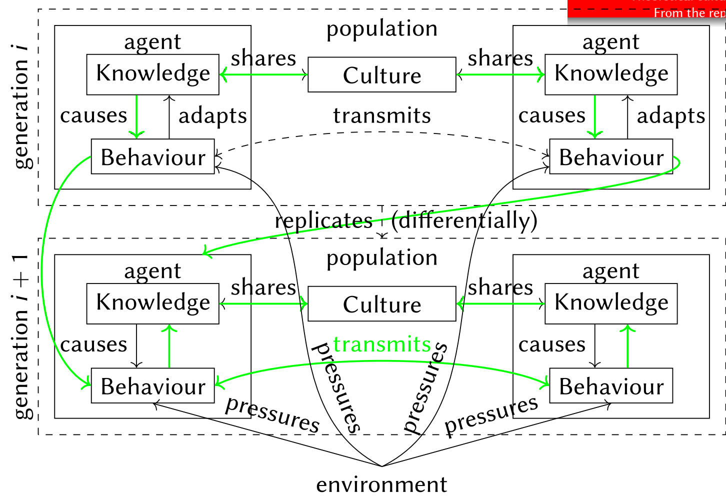
Knowledge transmission, population, culture



Embedded populations



Generation and vertical knowledge transmission



Conclusion

- Agent knowledge can evolve
- through continuous use and adaptation
- depending on other agents and environment

- Cultural knowledge evolution
- is *not* exclusive of other approaches

There are many exciting perspectives:

- Some that I already mentioned
- Connection with machine learning
- Links with social sciences and the humanities

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