Explaining *Aha!* moments in artificial agents through IKE-XAI: Implicit Knowledge Extraction for eXplainable AI

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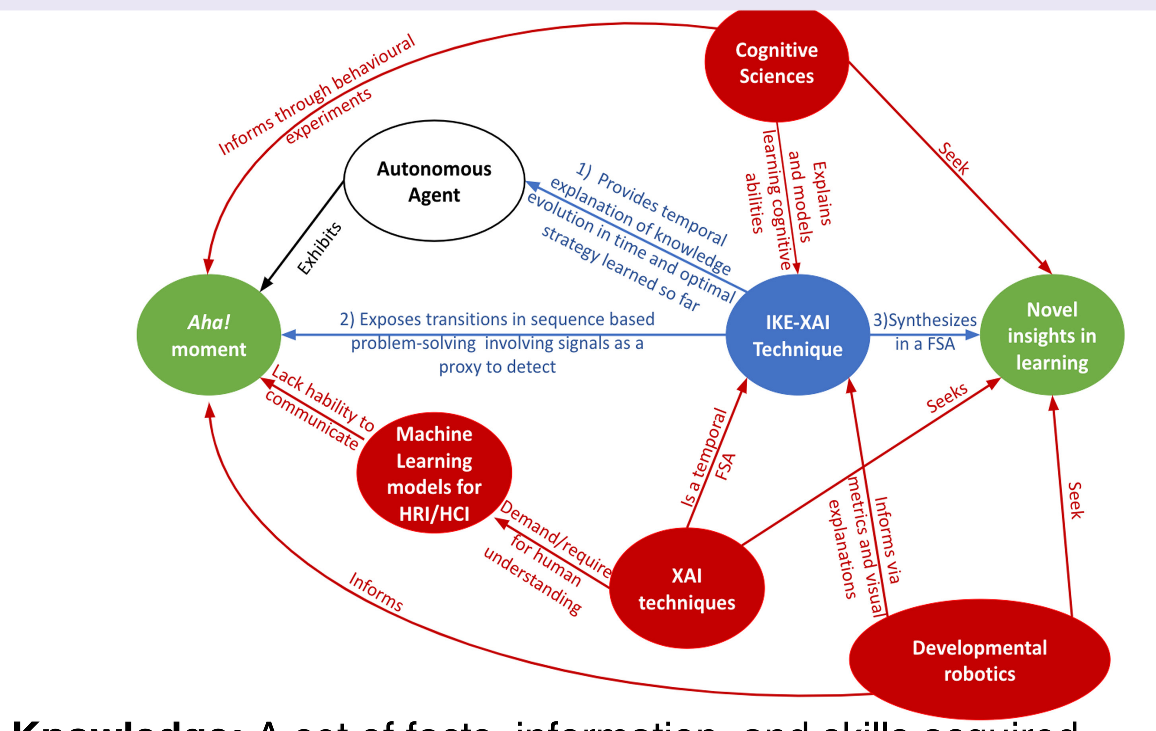
Abstract

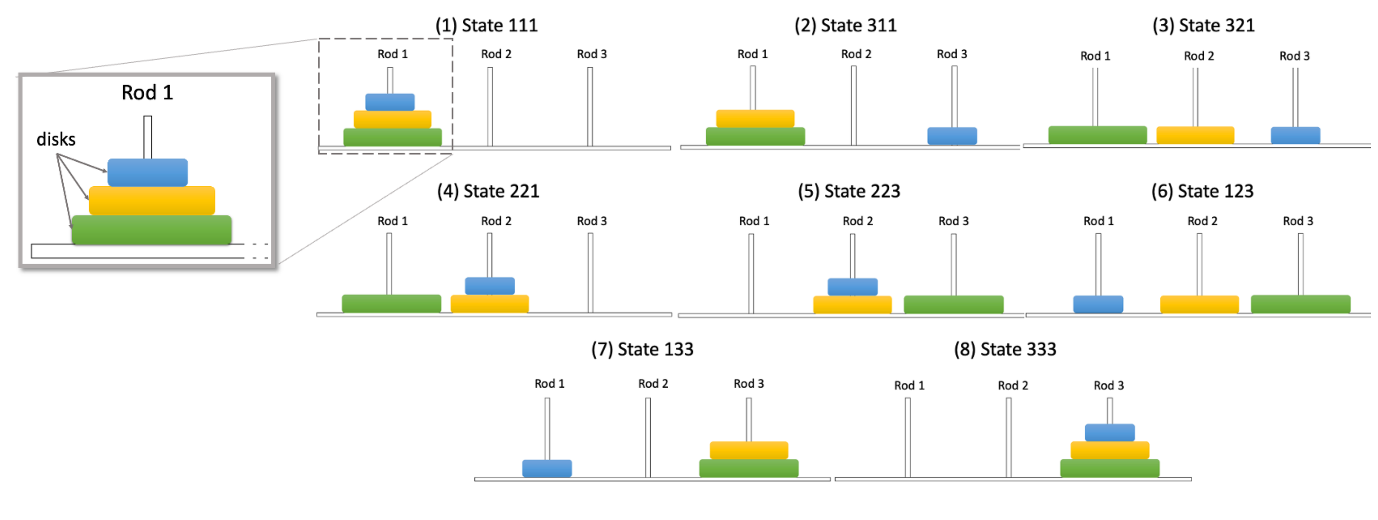
During the learning process, a child develops a mental representation of the task he or she is learning. A Machine Learning algorithm develops a latent representation of the task it learns. We investigate the development of the knowledge construction of an artificial agent (AA) by getting inspiration from the one of children. Our main contribution is **a 3-step methodology named Implicit Knowledge Extraction with eXplainable Artificial Intelligence (IKE-XAI) to extract the implicit knowledge, in form of an automaton, encoded by an artificial agent (AA) during its learning**. We showcase this technique to solve and explain the Tower of Hanoï (TOH) task when researchers have only access to sequences of moves that represent **observational behavior as in human–machine interaction**. Our approach combines: 1) a Q-learning agent that learns to perform the TOH task; 2) a trained LSTM recurrent neural network that encodes an implicit representation of the TOH task; and 3) an XAI process using a post-hoc implicit rule extraction algorithm to extract finite state automata. We propose using **graph representations as visual and explicit explanations of the behavior of the Q-learning agent**. Our experiments show that the IKE-XAI approach helps understanding the development of the Q-learning agent behavior by providing a **global explanation of its knowledge evolution during learning**. IKE-XAI also allows researchers to identify the **agent's *Aha!* moment** by determining from what moment the knowledge representation stabilizes and the agent no longer learns. This work is published in Neural Network journal (DOI=10.1016/j.neunet.2022.08.002) available at the QR code above.

Context

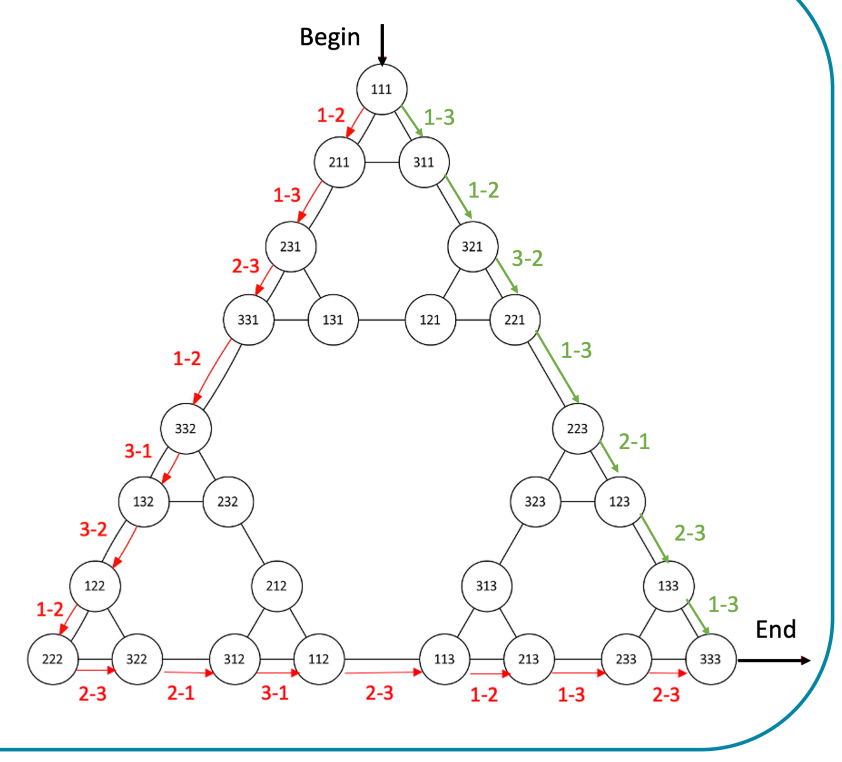


Knowledge: A set of facts, information, and skills acquired through experience by the AA that contribute to gaining a theoretical or practical understanding of a subject or the world.

Use case: the TOH with N = 3 disks

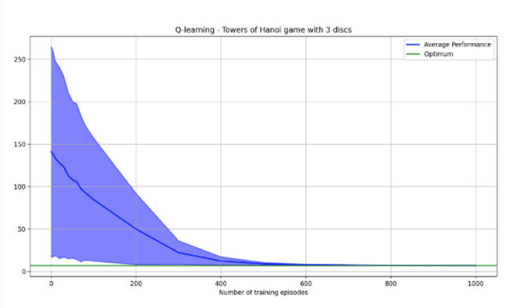


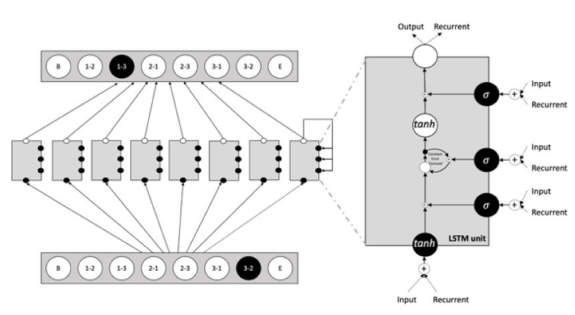
(a) Sequence of visited states	111, 311, 321, 221, 223, 123, 133, 333
(b) Sequence of moves	1-3 , 1-2, 3-2, 1-3, 2-1, 2-3, 1-3
(c) Sequence of moves encapsulated	B, 1-3, 1-2, 3-2, 1-3, 2-1, 2-3, 1-3, E

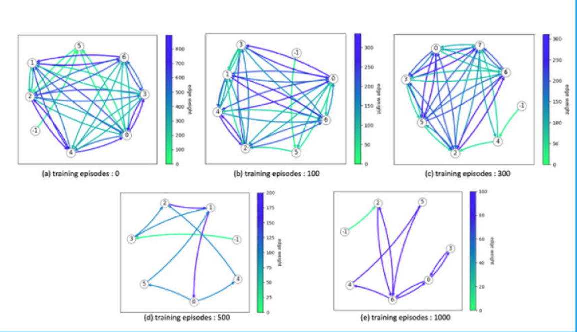


IKE-XAI methodology : Implicit Knowledge Extraction for eXplainable AI

FIELDS of RESEARCH	Developmental Robotics : Machine learning	Cognitive developmental psychology : Piaget's concrete operational stage	EXplainable AI: Sequence Models Graphical Summary Representation.
USE CASE	Towers of Hanoï - Concrete Problem Solving - Means-ends heuristics (General Problem Solver - Newell & Simon, 1972)		
	- STEP 1 -	- STEP 2 -	- STEP 3 -
EXPERIMENTAL PROTOCOL	Reinforcement learning phase : Exploration and Training	Sequence learning phase: Implicit rule encoding	XAI phase : Understanding the AA learning process
	AA – QLearning Agent Recording of number of movements	Trained LSTM model* AA sequences of movements	Post-hoc Rule extraction process and graph visualisation techniques Data set of recorded hidden patterns
RAW DATA obtained	Extraction of AA sequences of movements	Data set of recorded hidden patterns	Graphs of AA behavior at different stage of training
RESULTS	**An AA trained to perform TOH** whose behavior is observable through its movements sequences	**A trained LSTM model having developed a latent representation of the TOH** including all possible actions and their resulting states	**Accurate and specific graphical representations** for a targeted audience = AI researchers (Dev. robotics community)







* Trained LSTM model : a RNN with LSTM units that learned sequences of moves generated from Towers of Hanoï **to predict the next move according the past and current ones**

Experimental design of the IKE-XAI methodology to make explicit the process of the AA knowledge construction in three steps:

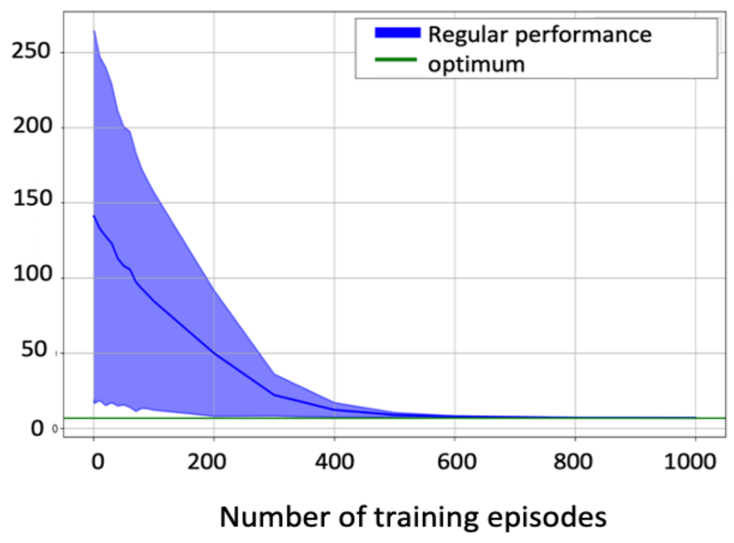
STEP (1) RL Phase: a **Q-learning agent** learns to perform the TOH task. At several stages of the learning process, the training process is suspended to make a recording of the AA's move sequences while it plays after learning. This step obtains:
(a) sequences of moves and
(b) an AA trained to perform TOH whose behavior is observable through its sequences of moves, to inform the solution chosen by the AA to reach the solution state (i.e., sequences of moves).

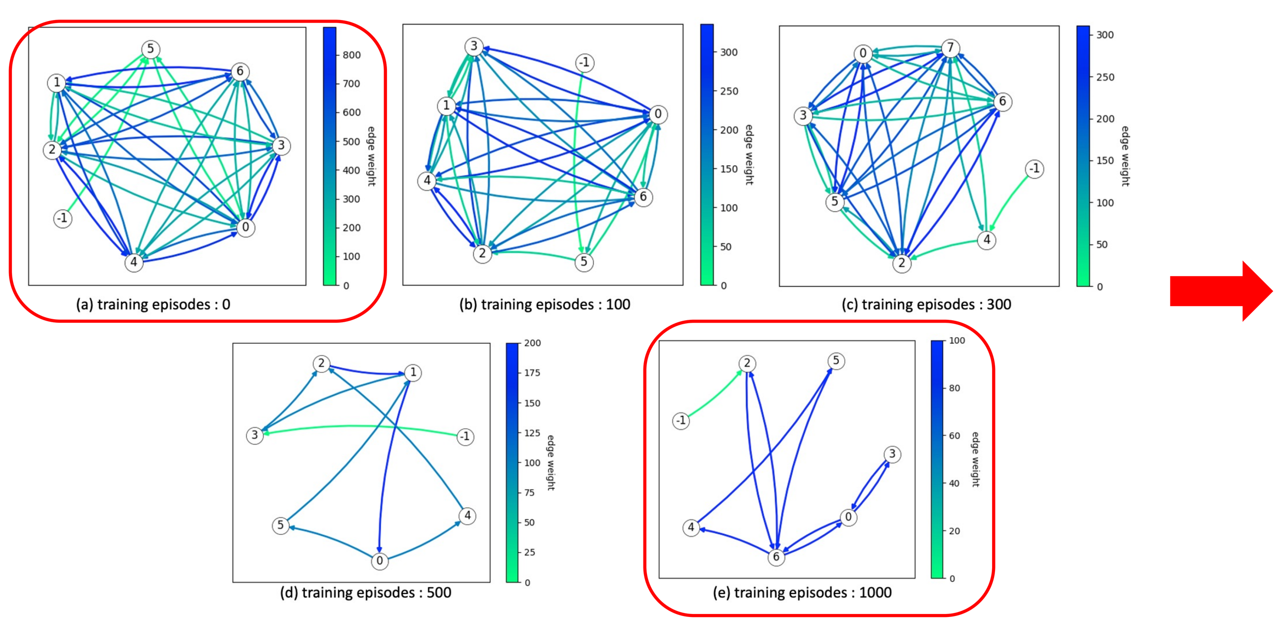
STEP (2) Moves Sequence Learning Phase: the recorded sequences of moves of the AA are fed to train an **LSTM model** to predict the AA's next move at time t based on the current and past ones. This step returns a dataset of recordings of hidden patterns (i.e., the activity vectors of the hidden layer generated by the network at each input). The trained LSTM model had encoded an implicit representation of the TOH rules due to the learned sequences. Let us note that the trained LSTM model is trained on sequences generated from the TOH abstract representation

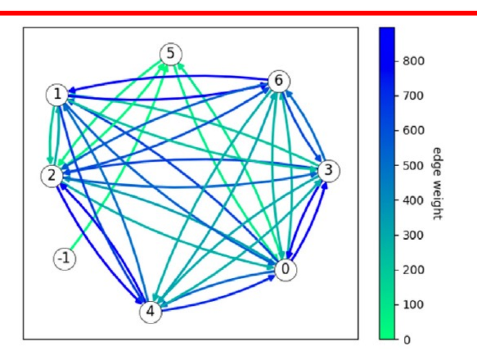
STEP (3) XAI Phase: a **post-hoc implicit rule extraction algorithm** and a graph visualization technique are applied to the dataset of recorded hidden patterns to extract graphs of AA behavior at different stages of training.

Experiments & Results

The TOH with N = 3 disks:

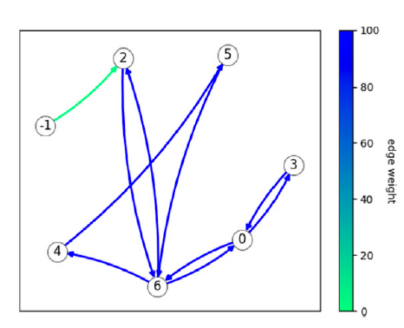






FSA Edge (source node - target node)	Associated action (move)	Computed weight
"-1" - 5	B	1
5 - 0	"1-3"	58
5 - 2	"1-2"	42
0 - 3	"3-1"	882
0 - 2	"1-2"	335
0 - 6	"2-3"	261
0 - 4	"2-1"	538
0 - 1	"3-2"	658
0 - 5	B	82
0 - 0	"1-3"	20
3 - 2	"1-2"	650

(a) training episode:0 (truncated table)



FSA Edge (source node - target node)	Associated action (move)	Computed weight
"-1" - 111	B	1
2 - 6	"1-3"	100
6 - 4	"1-2"	100
4 - 5	"3-2"	100
5 - 6	"1-3"	100
6 - 0	"2-3"	100
0 - 3	"3-1"	100
3 - 0	"2-3"	100
0 - 6	"1-3"	100
6 - 2	B	99

(e) training episode:1000

Experiments on TOH with variable N disks:

	N = 3	N = 4	N = 6
Optimal number of moves 2^N-1	7	15	63
Number of nodes	27	81	729
Number of edges	39	120	1092
Aha! moment (average number of training episodes)	500	3000	100000
Average length of sequences at the beginning of training	159	800	21500
Average length of sequences after the Aha! moment	9	15	63

Main findings

IKE-XAI, a post-hoc explainable methodology that provides a **visual model-agnostic explanation based on the observational behavior of an AA**, allows to:

- Extract **the vision of the AA of a task** (simple and complex one) using a sequence learning model
- Extract **knowledge, in the form of FSA** that represents **AA's problem-solving strategies**, even not optimal ones, for their explainability.
- Make explicit **the behavioral changes of an AA** due to the analysis of the edge weights of the extracted automata, i.e. the **transformation of its expertise** in solving the task.
- Identify the shift in the AA's behavior from exploration to exploitation i.e., ***Aha! moment*** for the agent and the Aha! moment for the researcher when he/she understands when it happens

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