

Abstract

State Reduction Problem for Redundant Observations and Goal-Oriented Reinforcement Learning Environment Inference

Kazuki Takahshi

Graduate School of Informatics, Kogakuin University

Humans are able to perceive the world through sensory information, learn through trial and error, and perform appropriate actions step by step. In particular, humans can effectively process visual information and extract information useful for achieving their goals while solving tasks that require long-term procedural planning. Developing such highly intelligent agents could automate hazardous and high-precision tasks effectively.

To realize a practical agent for real-world tasks, two main technical challenges must be addressed: extracting useful information from complex information, and controlling behavior to achieve goals. The agent should also prioritize sample efficiency to adapt with minimal trial and error. Additionally, to ensure users feel comfortable using the agent, explainability of the agent’s behavioral principles is crucial.

Deep reinforcement learning approach, which combines information processing by deep learning and action control by reinforcement learning, can be applied to a wide range of tasks by black-boxing the causal structure of useful information. However, black-boxing the causal structure has the disadvantage that it not only requires a lot of trial-and-error for learning, but also makes the agent’s behavioral principles opaque.

In contrast, Bayesian inference, which directly models the causal structure of all information, can substitute for information processing to achieve high sample efficiently learning. Modeling the causal structure also provides a high explainability because it allows us to predict the future impact of the agent’s actions. However, this approach still has implementation challenge, as it considers all information and requires a large amount of memory to process the complex information.

In the real world, information comprises both useful and irrelevant details for achieving goals. Therefore, if only useful information can be extracted from complex information and its concise causal structure can be modeled, the implementation challenge of memory requirements can be reduced. In addition, the concise causal structure has the advantage of being easier for people to understand the agent’s behavioral principles.

Therefore, this paper defines a state reduction problem that integrates the extraction of useful information from complex data into learning within a reinforcement learning framework. It proposes two approaches to address this challenge. The first approach employs dimensionality reduction using information structure, allowing state reduction to represent complex information in a low-dimensional space. The second approach utilizes environment inference via information generation processes, enabling state reduction to extract more valuable information by considering the causal structure of time series. Results demonstrate the robustness of these methods in state reduction and their capability to quickly adapt to tasks. Both approaches address the state reduction problem under different constraints and can combine preprocessing by dimensionality reduction with subsequent environmental inference for state reduction. This enhances scalability and explainability of complex information, crucial for future real-world applications.