Reinforcement Learning: DRL

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Contents

DECSAI

Partial Observability

The state is not fully known => Partially Observable Markov Decision Process (POMDP)

The process is decomposed into an MDP + a state estimator/compressor

Imitation Learning

There is historical data available about past (expert) decisions and limited access to the environment

Train the agent network from historical data => consider unseen situations! (inverse RL, generative models)

Hierarchical Reinforcement Learning

A problem is decomposed into subtasks to reduce the search space

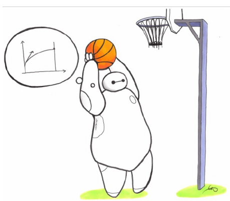
Train a policy for each subtask and define a high-level policy => Detecting subtasks can be challenging

Multi-Agent Reinforcement Learning

Sequential decision-making of many (autonomous) agents => Markov Games and Extensive-Form Games

Many architectures and interactions are possible: centralized vs decentralized, cooperative vs competitive

Libraries



Stable Baselines https://stable-baselines.readthedocs.io/

↑ The most used library, including implementations in PyTorch of the most common DRL algorithms

↓ Difficult to customise

Clean RL https://docs.cleanrl.dev/

↑ Simple, hassle-free implementation of PyTorch DRL algorithms intended for teaching and researching purposes

↓ Less established than stable-baselines

RLlib https://docs.ray.io/en/latest/rllib/index.html

↑ Intended for production-level, high-performance and parallel DRL implementations based on the Ray framework

↓ More complex

Acme https://dm-acme.readthedocs.io/en/latest/

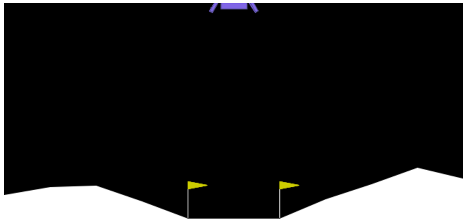
↑ Backed by Google DeepMind, state-of-the-art algorithms

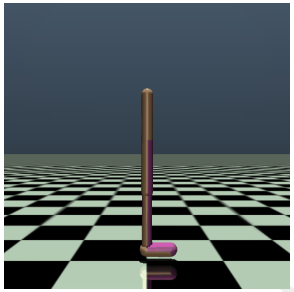
↓ Less frequently updated

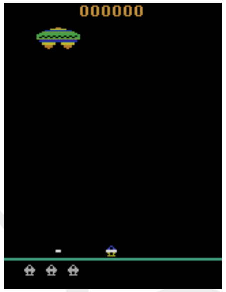
Environments

Gymnasium https://gymnasium.farama.org

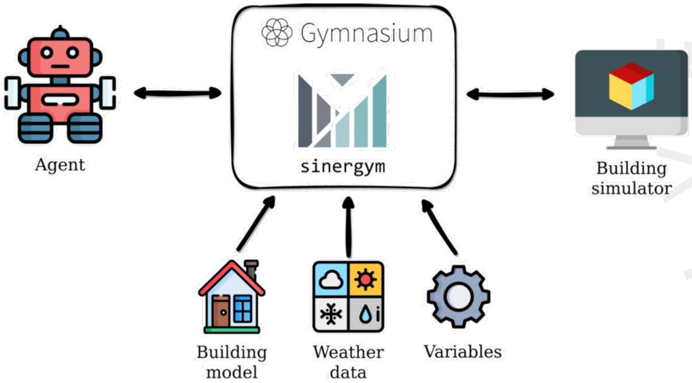
Standard API + collection of sample environments







Sinergym https://ugr-sail.github.io/sinergym/



(D)RL is typically used for continuous control

Alternative to classic methods, e.g., rule-based controllers (RBC), proportional-integral-derivative controllers (PID), model predictive controllers (MPC)

↑ Longer-term control horizons

↑ Does not need heuristic knowledge

↑ Does not need a fine-grained model of the environment

↓ Requires a model of the environment

↓ Learning may be unstable

↓ Too complex to train

? Transferability from problem to problem

? Continuous learning

? Multi-agent emergent behaviour

? Explainability

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Challenges of real-world reinforcement learning: definitions, benchmarks and analysis

Gabriel Dulac-Arnold, Nir Levine, Daniel J. Mankowitz, Jerry Li, Cosmin Paduraru, Sven Gowal & Todd Hester

Machine Learning **110**, 2419–2468 (2021) | Cite this article

Abstract

Reinforcement learning (RL) has proven its worth in a series of artificial domains, and is beginning to show some successes in real-world scenarios. However, much of the research advances in RL are hard to leverage in real-world systems due to a series of assumptions that are rarely satisfied in practice. In this work, we identify and formalize a series of independent challenges that embody the difficulties that must be addressed for RL to be commonly deployed in real-world systems. For each challenge, we define it formally in the context of a Markov Decision Process, analyze the effects of the challenge on state-of-the-art learning algorithms, and present some existing attempts at tackling it. We believe that an approach that addresses our set of proposed challenges would be readily deployable in a large number of real world problems. Our proposed challenges are implemented in a suite of continuous control environments called `realworldrl-suite` which we propose an as an open-source benchmark.

Ten questions concerning reinforcement learning for building energy management

Zoltan Nagy [a], Gregor Henze [b d], Sourav Dey [b], Javier Arroyo [c], Lieve Helsen [c], Xiangyu Zhang [d], Bingqing Chen [e], Kadir Amasyali [f], Kuldeep Kurte [f], Ahmed Zamzam [d], Helia Zandi [f], Ján Drgoňa [g], Matias Quintana [h n], Steven McCullogh [i], June Young Park [i], Han Li [j], Tianzhen Hong [j], Silvio Brandi [k], Giuseppe Pinto [l k], Alfonso Capozzoli [k]… Andrey Bernstein [d]

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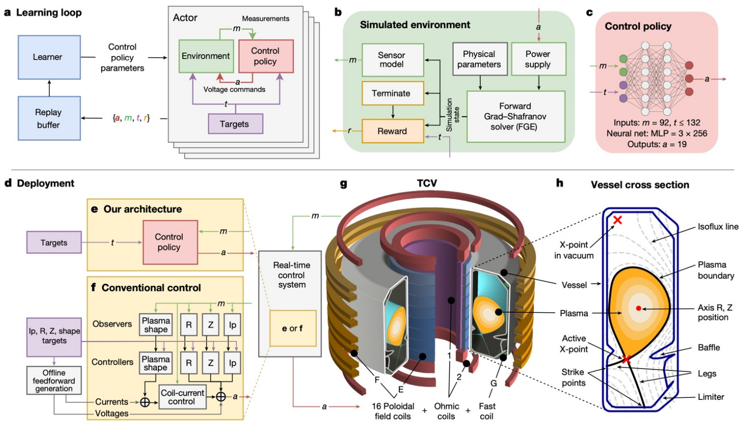
Abstract

As buildings account for approximately 40% of global energy consumption and associated greenhouse gas emissions, their role in decarbonizing the power grid is crucial. The increased integration of variable energy sources, such as renewables, introduces uncertainties and unprecedented flexibilities, necessitating buildings to adapt their energy demand to enhance grid resiliency. Consequently, buildings must transition from passive energy consumers to active grid assets, providing demand flexibility and energy elasticity while maintaining occupant comfort and health. This fundamental shift demands advanced optimal control methods to manage escalating energy demand and avert power outages. Reinforcement learning (RL) emerges as a promising method to address these challenges. In this paper, we explore ten questions related to the application of RL in buildings, specifically targeting flexible energy management. We consider the growing availability of data, advancements in machine learning algorithms, open-source tools, and the practical deployment aspects associated with software and hardware requirements. Our objective is to deliver a comprehensive introduction to RL, present an overview of existing research and accomplishments, underscore the challenges and opportunities, and propose potential future research directions to expedite the adoption of RL for building energy management.

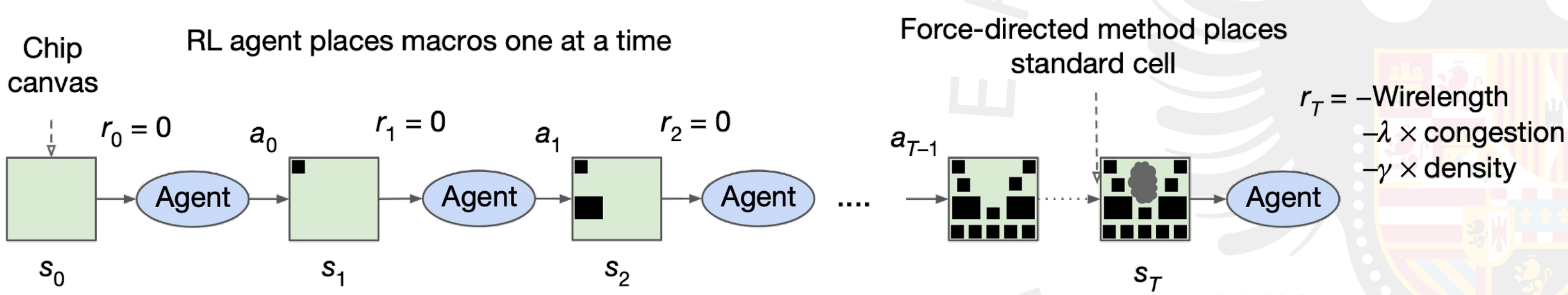
G. Dulac-Arnold et al. (2021) *Challenges of real-world reinforcement learning: definitions, benchmarks and analysis.* Machine Learning 110, 2419-2468.

Z. Nagy et al. (2023) *Ten questions concerning reinforcement learning for building energy management.* Building and Environment 241, 110435.

(D)RL is being applied successfully!



J. Degrave et al. (2022) *Magnetic control of tokamak plasmas through deep reinforcement learning.* Nature 602, 414-419.

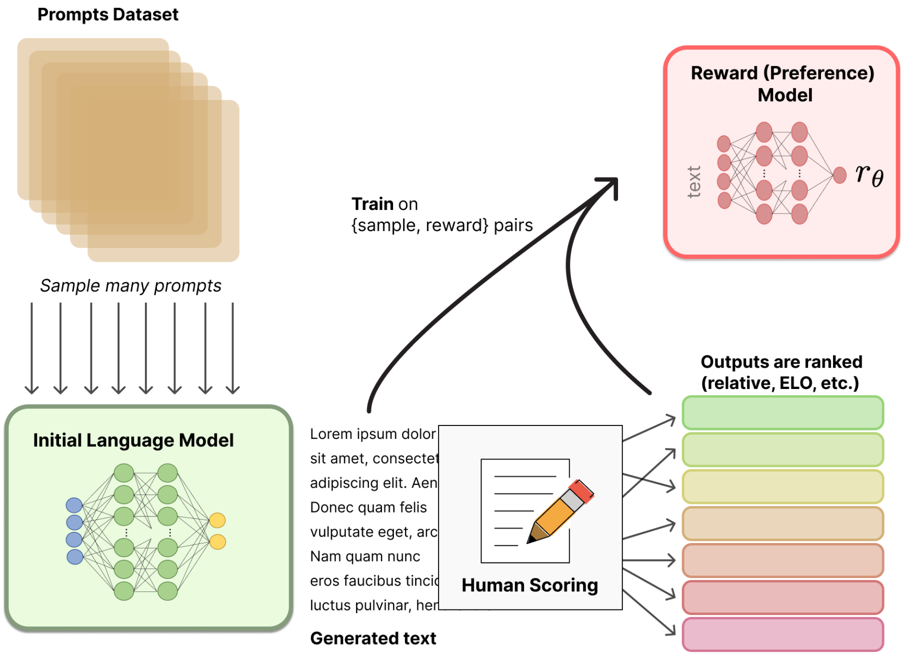


A. Mirhoseini et al. (2021) *A graph placement methodology for fast chip design.* Nature 594, 207-212.

(D)RL is being applied in other problems!

Reinforcement Learning from Human Feedback (RLHF)

Key component of chatbots to improve query-answering in large language models



N. Lambert et al. (2022) *Illustrating Reinforcement Learning from Human Feedback (RLHF).* https://huggingface.co/blog/rlhf