UNIVERSITY OF TECHNOLOGY
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CHEMNITZ

Deep Reinforcement Learning

Outlook

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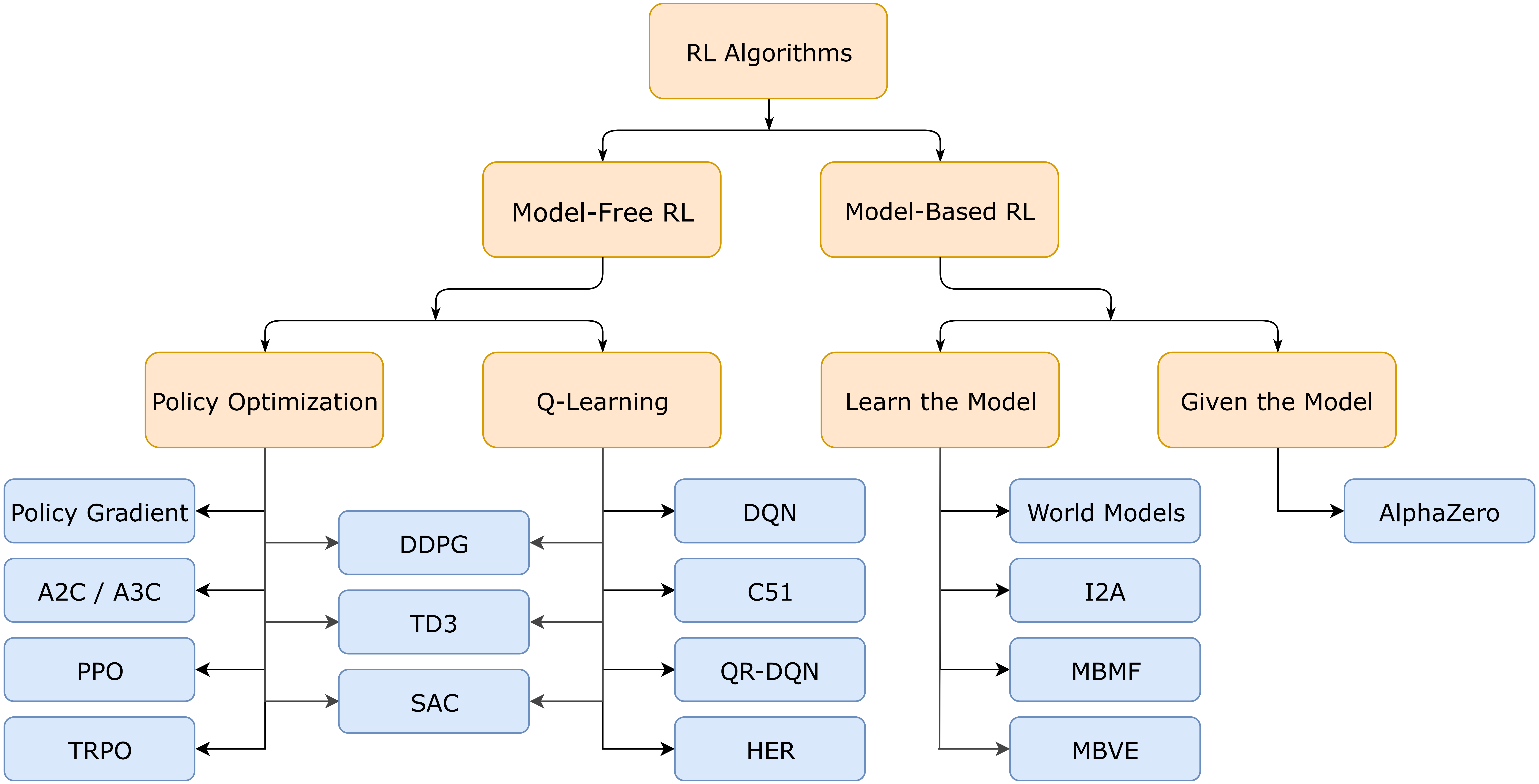
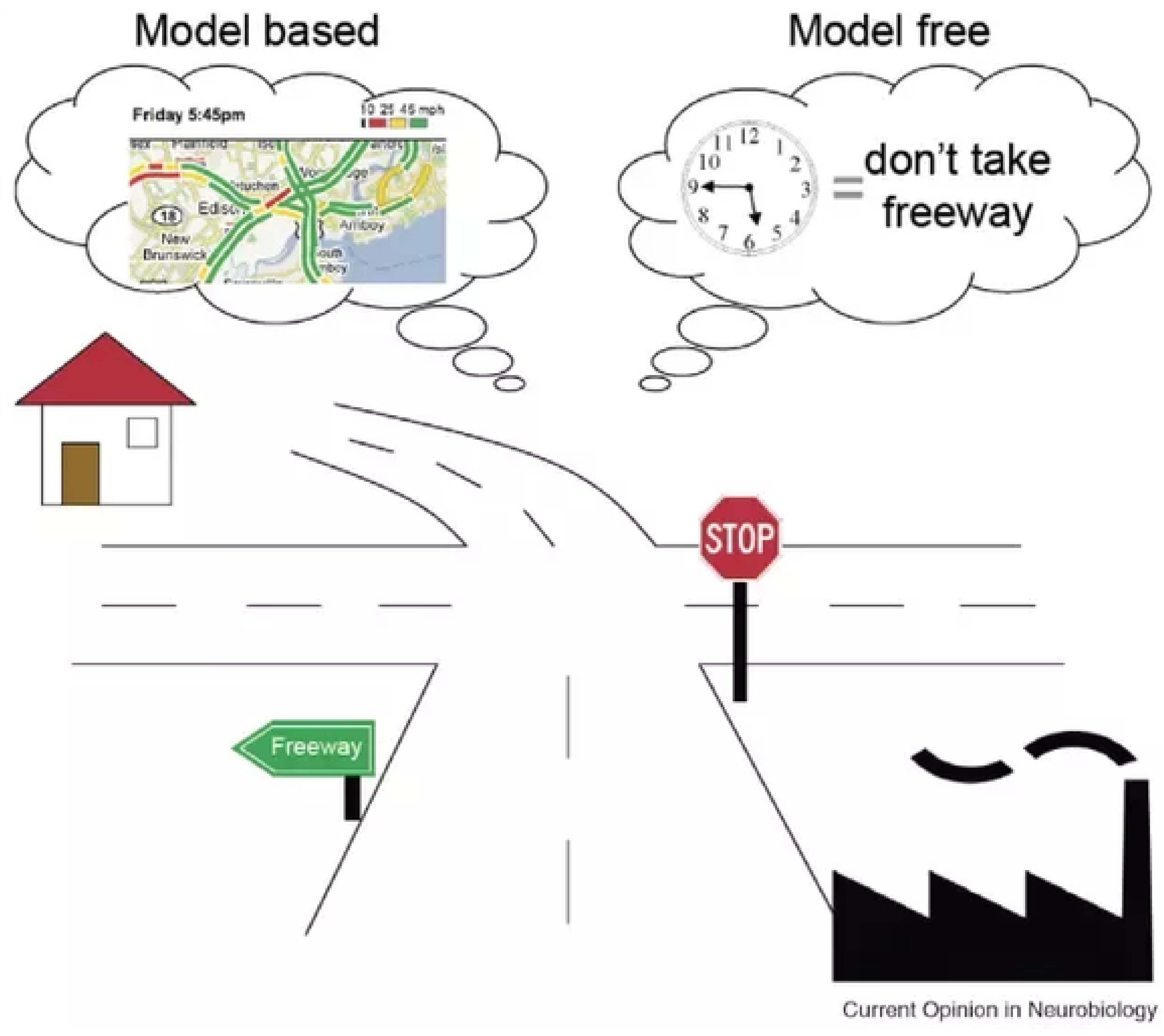
1 - Summary of DRL

Overview of deep RL methods

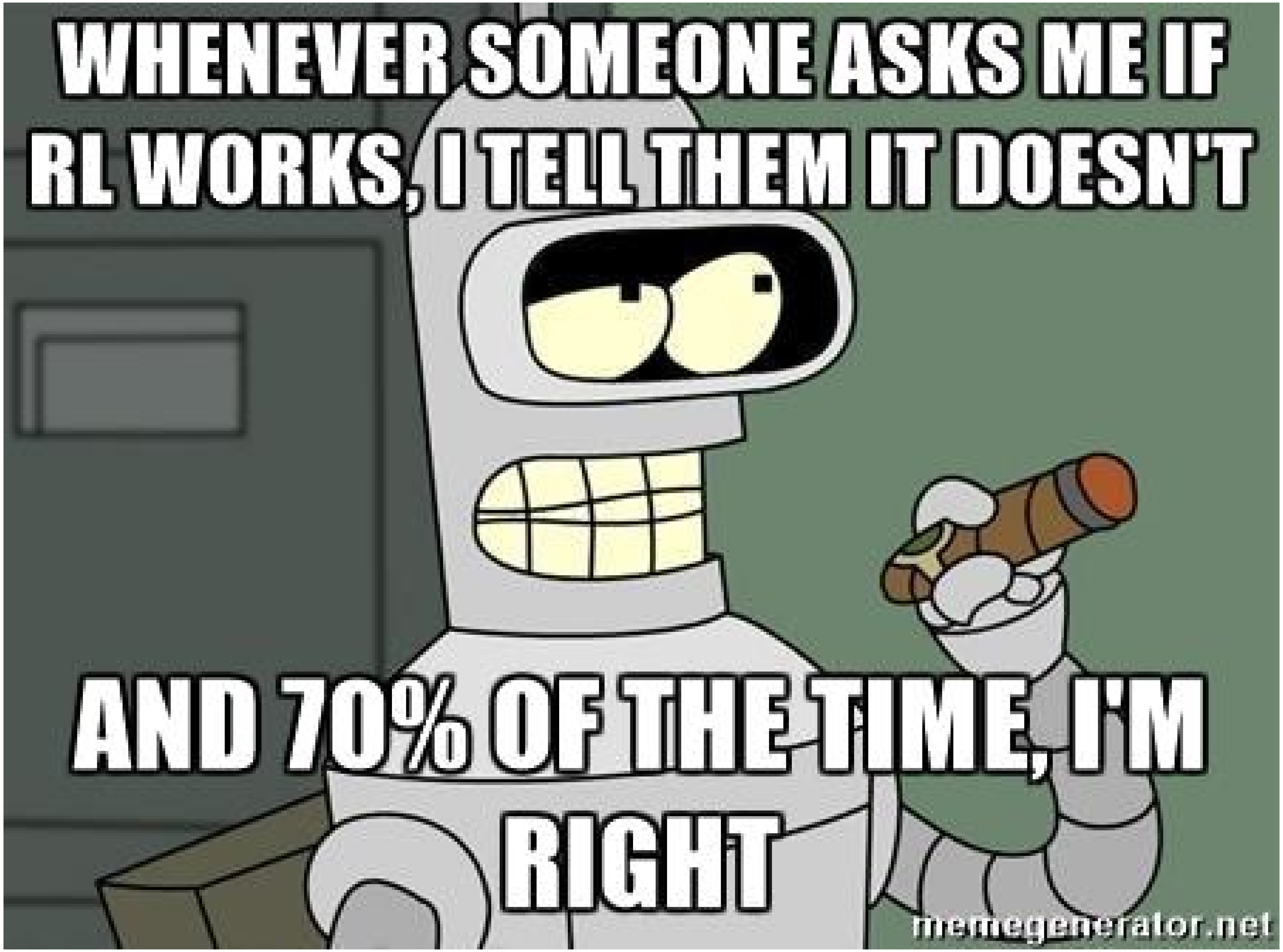


Source: https://github.com/avillemin/RL-Personnal-Notebook

Overview of deep RL methods



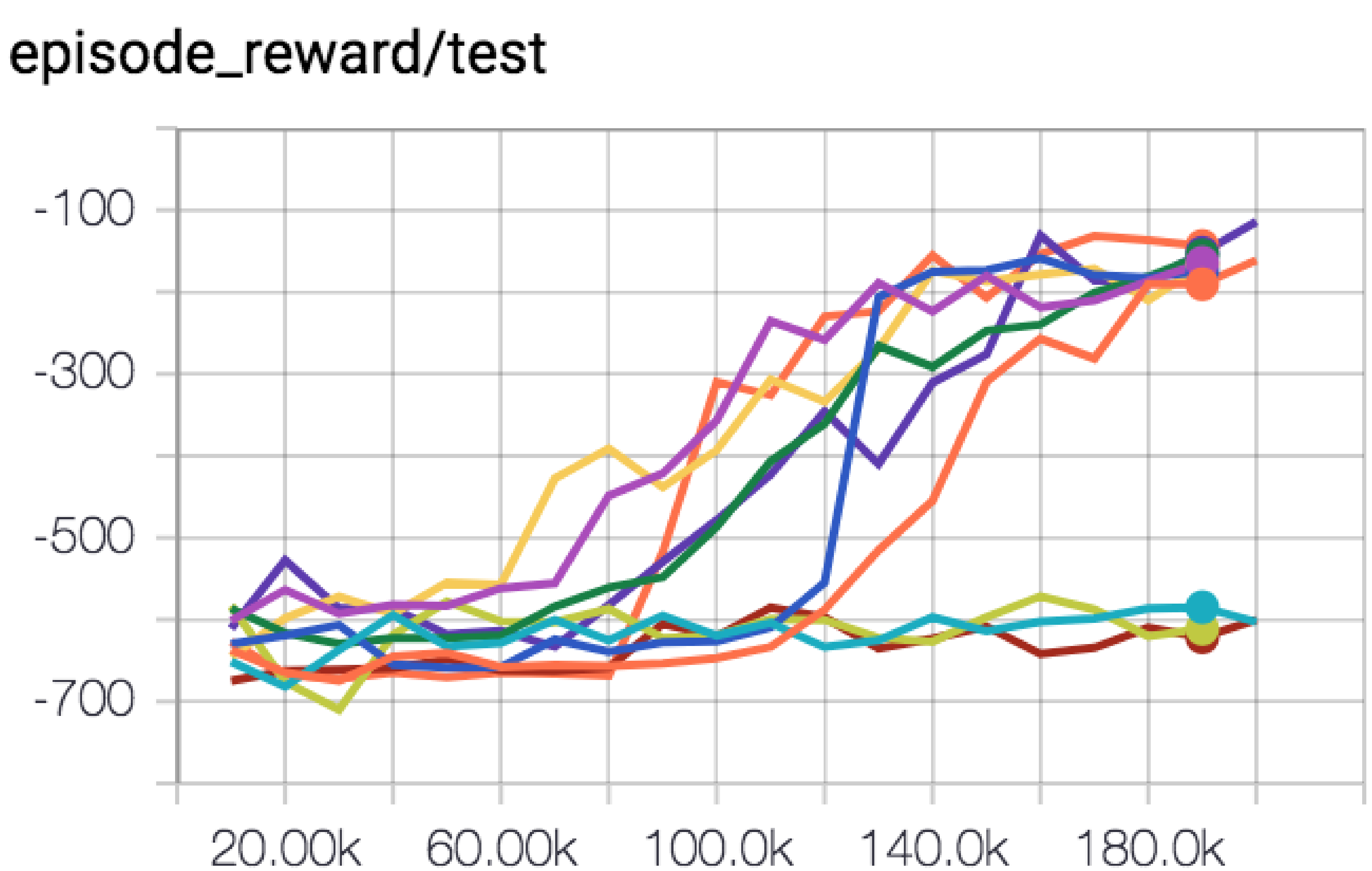
- **Model-free methods** (DQN, A3C, DDPG, PPO, SAC) are able to find optimal policies in complex MDPs by just **sampling** transitions.
- They suffer however from a high **sample complexity**, i.e. they need ridiculous amounts of samples to converge.
- **Model-based methods** (I2A, Dreamer, MuZero) use **learned dynamics** to predict the future and plan the consequences of an action.
- The sample complexity is lower, but learning a good model can be challenging. Inference times can be prohibitive.

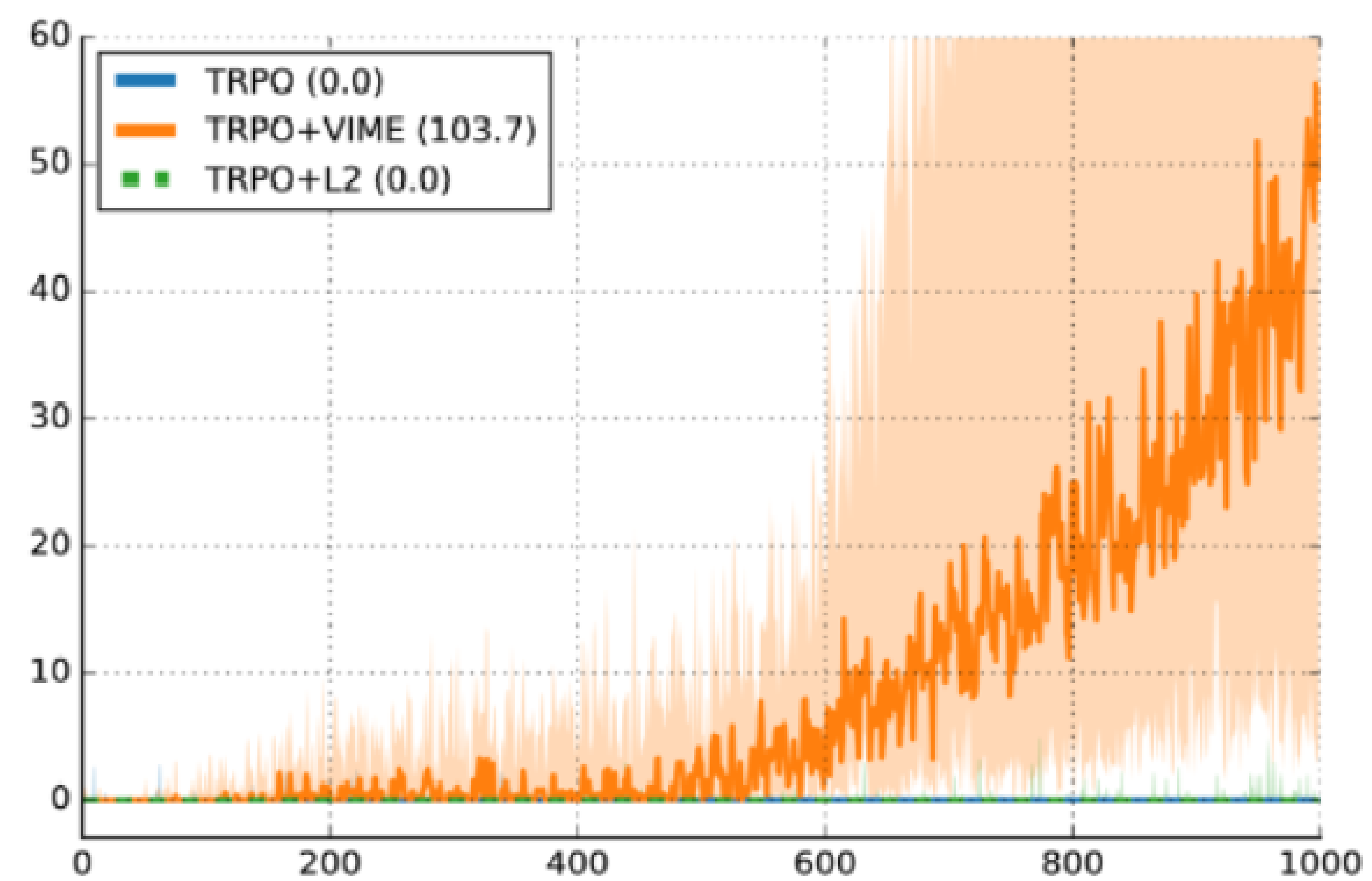


Source: https://www.alexirpan.com/2018/02/14/rl-hard.html

Deep RL is still very unstable

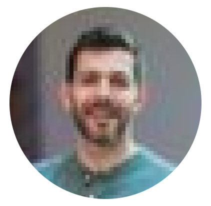
- Depending on initialization, deep RL networks may or may not converge (30% of runs converge to a worse policy than a random agent).
- Careful optimization such as TRPO / PPO help, but not completely.
- You never know if failure is your fault (wrong network, bad hyperparameters, bug), or just bad luck.





Source: https://www.alexirpan.com/2018/02/14/rl-hard.html

Deep RL lacks generalization to different environments



Jacob Andreas
@jacobandreas · **Follow**

Deep RL is popular because it's the only area in ML where it's socially acceptable to train on the test set.

9:27 PM · Oct 28, 2017

628 Reply Copy link

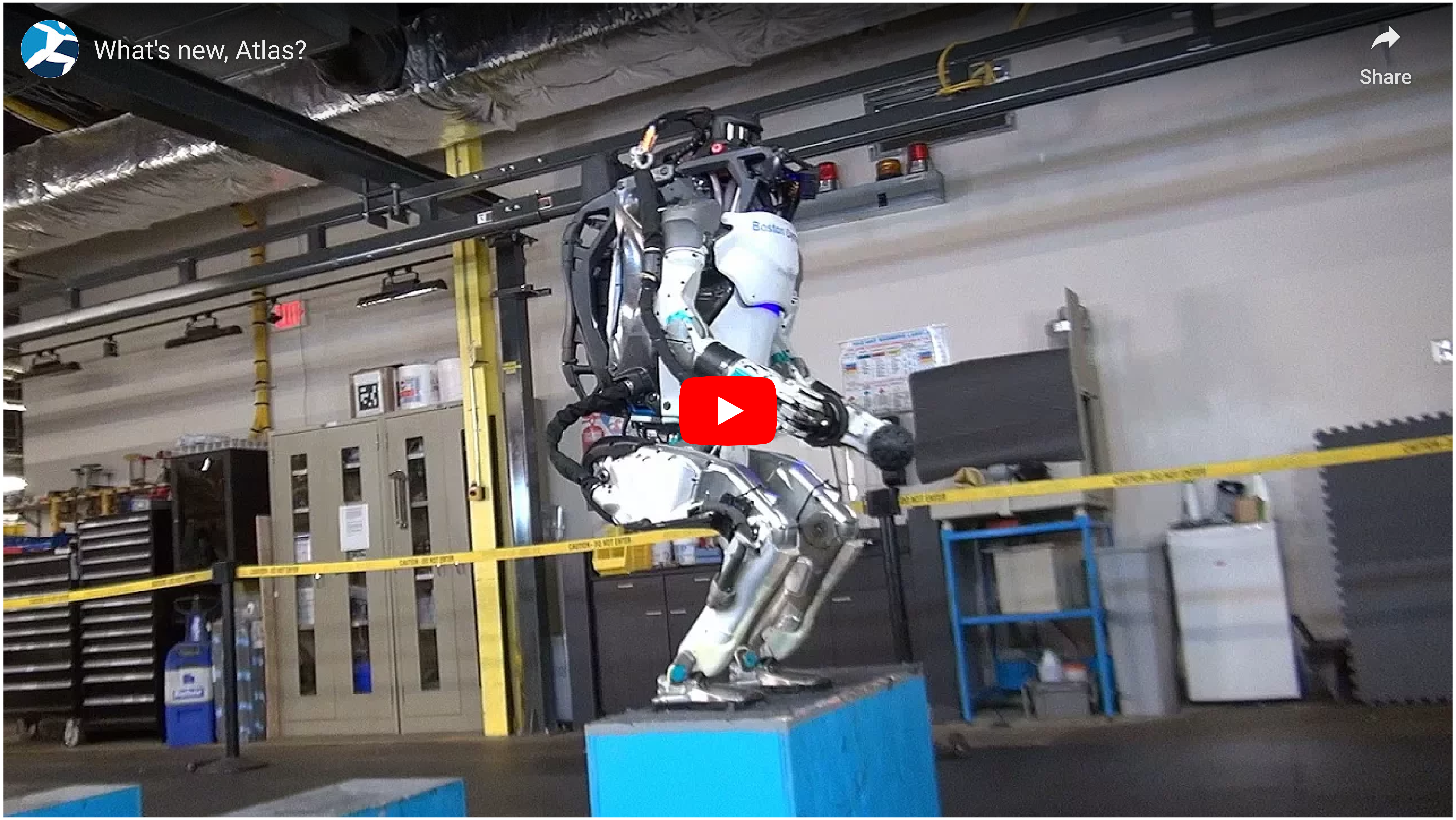
Read 13 replies

- As it uses neural networks, deep RL **overfits** its training data, i.e. the environment it is trained on.
- If you change anything to the environment dynamics, you need to retrain from scratch.
- OpenAI Five collects 900 years of game experience per day on Dota 2: it overfits the game, it does not learn how to play.
- Modify the map a little bit and everything is gone.
- But see Meta RL - RL^2 later.

Classical methods sometimes still work better

- Model Predictive Control (MPC) is able to control Mujoco robots much better than RL through classical optimization techniques (e.g. iterative LQR) while needing much less computations.
- If you have a good physics model, do not use DRL. Reserve it for unknown systems, or when using noisy sensors (images).
- Genetic algorithms (CMA-ES) sometimes give better results than RL to train policy networks.

You cannot do that with deep RL (yet)



RL libraries

- `keras-rl`: many deep RL algorithms implemented directly in keras: DQN, DDQN, DDPG, CEM...

https://github.com/matthiasplappert/keras-rl

- `OpenAI Baselines` from OpenAI: A2C, ACER, ACKTR, DDPG, DQN, PPO, TRPO... Not maintained.

https://github.com/openai/baselines

- `Stable baselines` from Inria Flowers, a clean rewrite of OpenAI baselines including SAC and TD3.

https://github.com/hill-a/stable-baselines

- `chainer-rl` implemented in Chainer: A3C, ACER, DQN, DDPG, PGT, PCL, PPO, TRPO.

https://github.com/chainer/chainerrl

- `RL Mushroom` is a very modular library based on Pytorch allowing to implement DQN and variants, DDPG, SAC, TD3, TRPO, PPO.

https://github.com/MushroomRL/mushroom-rl

RL libraries

- `Tensorforce` implement in tensorflow: DQN and variants, A3C, DDPG, TRPO, PPO.

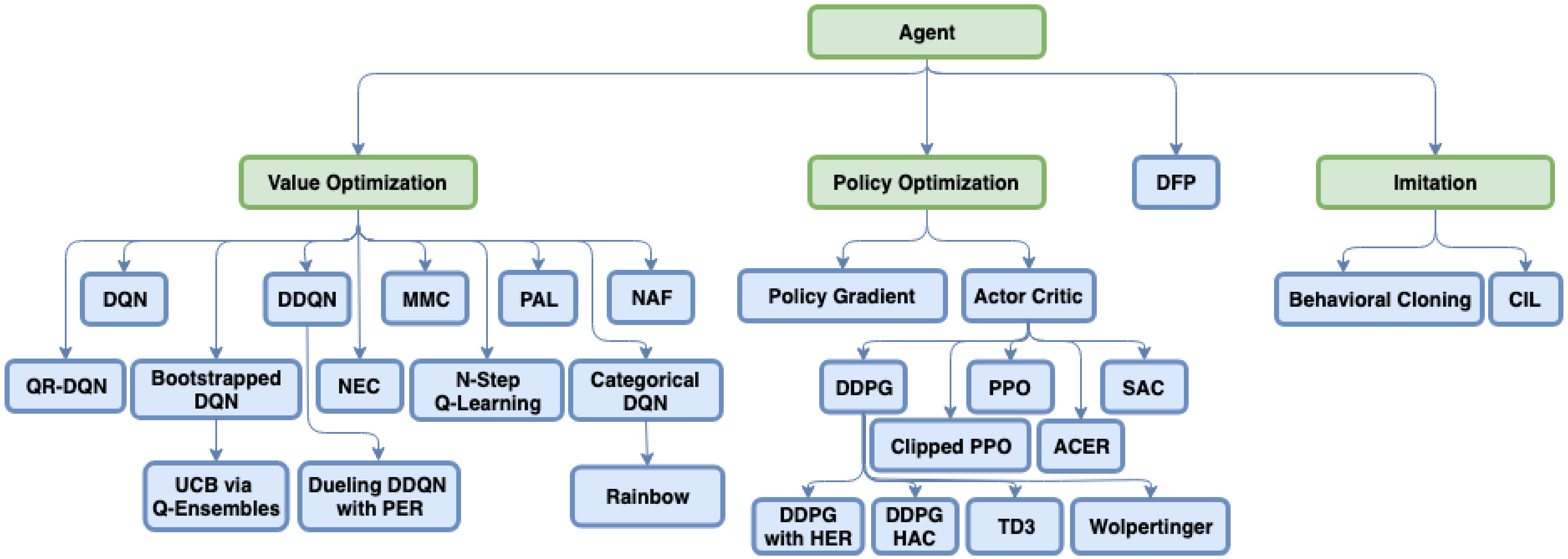
https://github.com/tensorforce/tensorforce

- `Tensorflow Agents` is officially supported by tensorflow: DQN, A3C, DDPG, TD3, PPO, SAC.

https://github.com/tensorflow/agents

- `Coach` from Intel Nervana also provides many state-of-the-art algorithms.

https://github.com/NervanaSystems/coach



Source: https://github.com/NervanaSystems/coach

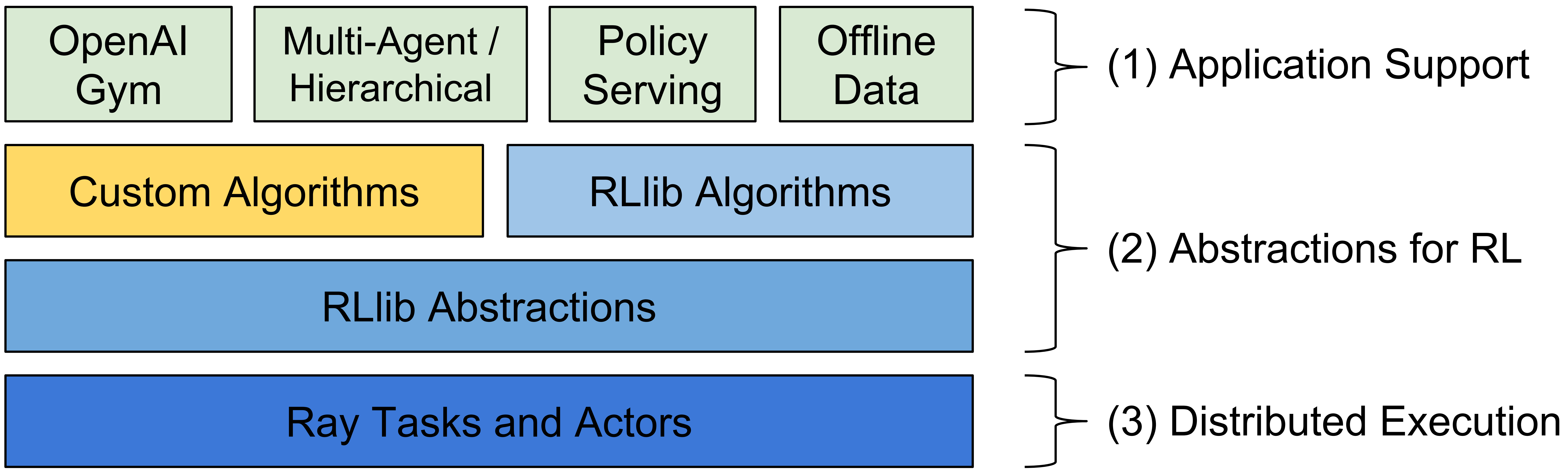
RL libraries

- `rllib` is part of the more global ML framework Ray, which also includes Tune for hyperparameter optimization.

It has implementations in both tensorflow and Pytorch.

All major model-free algorithms are implemented (DQN, Rainbow, A3C, DDPG, PPO, SAC), including their distributed variants (Ape-X, IMPALA, TD3) but also model-based algorithms (Dreamer!)

https://docs.ray.io/en/master/rllib.html

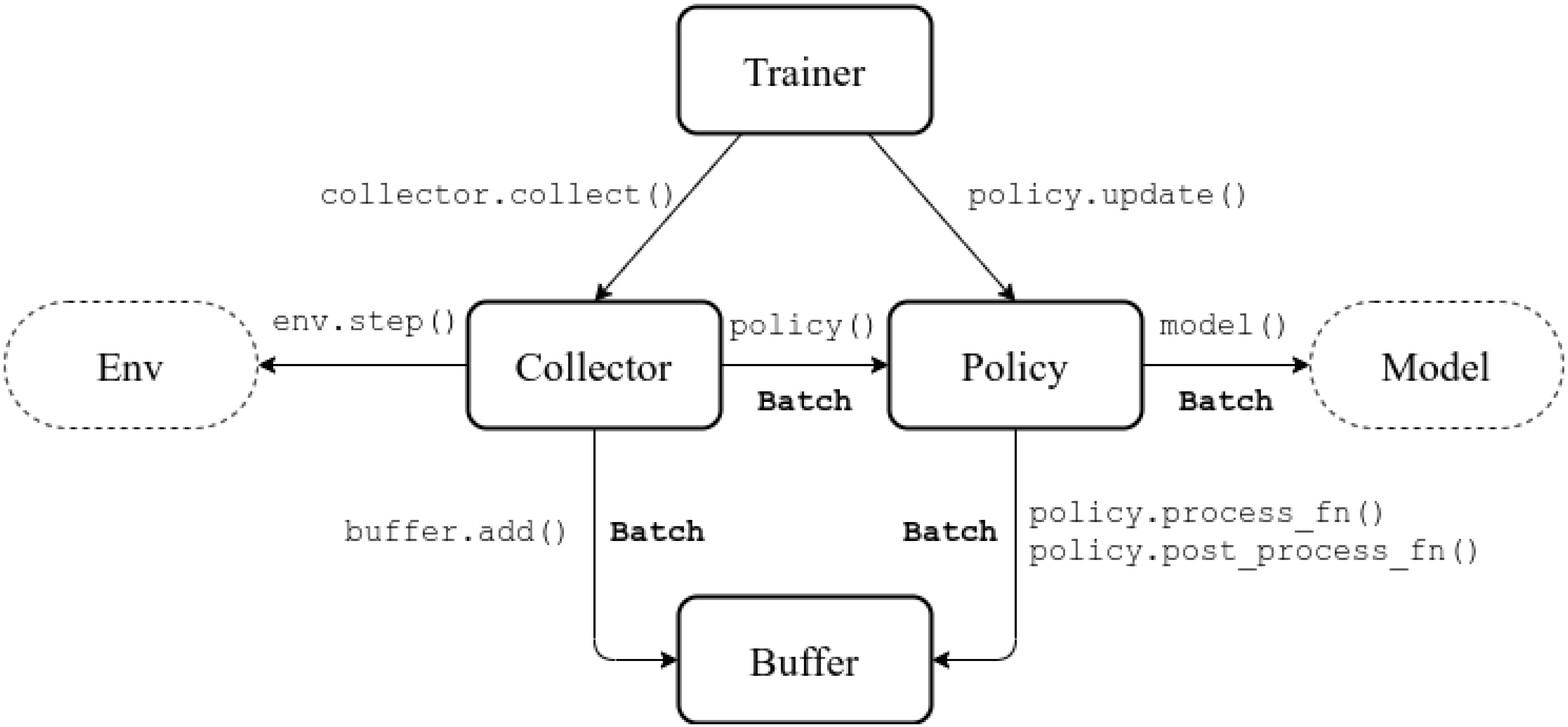


RL libraries

- `tianshou` is a recent addition to the family. The implementation is based on pytorch and is very modular. Allows for efficient distributed RL.

Algos: DQN+/DDPG/PPO/SAC, imitation learning, offline RL…

https://github.com/thu-ml/tianshou



2 - Inverse RL - learning the reward function

RL maximizes the reward function you give it

- RL is an optimization method: it maximizes the reward function that you provide it.
- If you do not design the reward function correctly, the agent may not do what you expect.
- In the Coast runners game, turbos provide small rewards but respawn very fast: it is more optimal to collect them repeatedly than to try to finish the race.

Reward functions need careful engineering

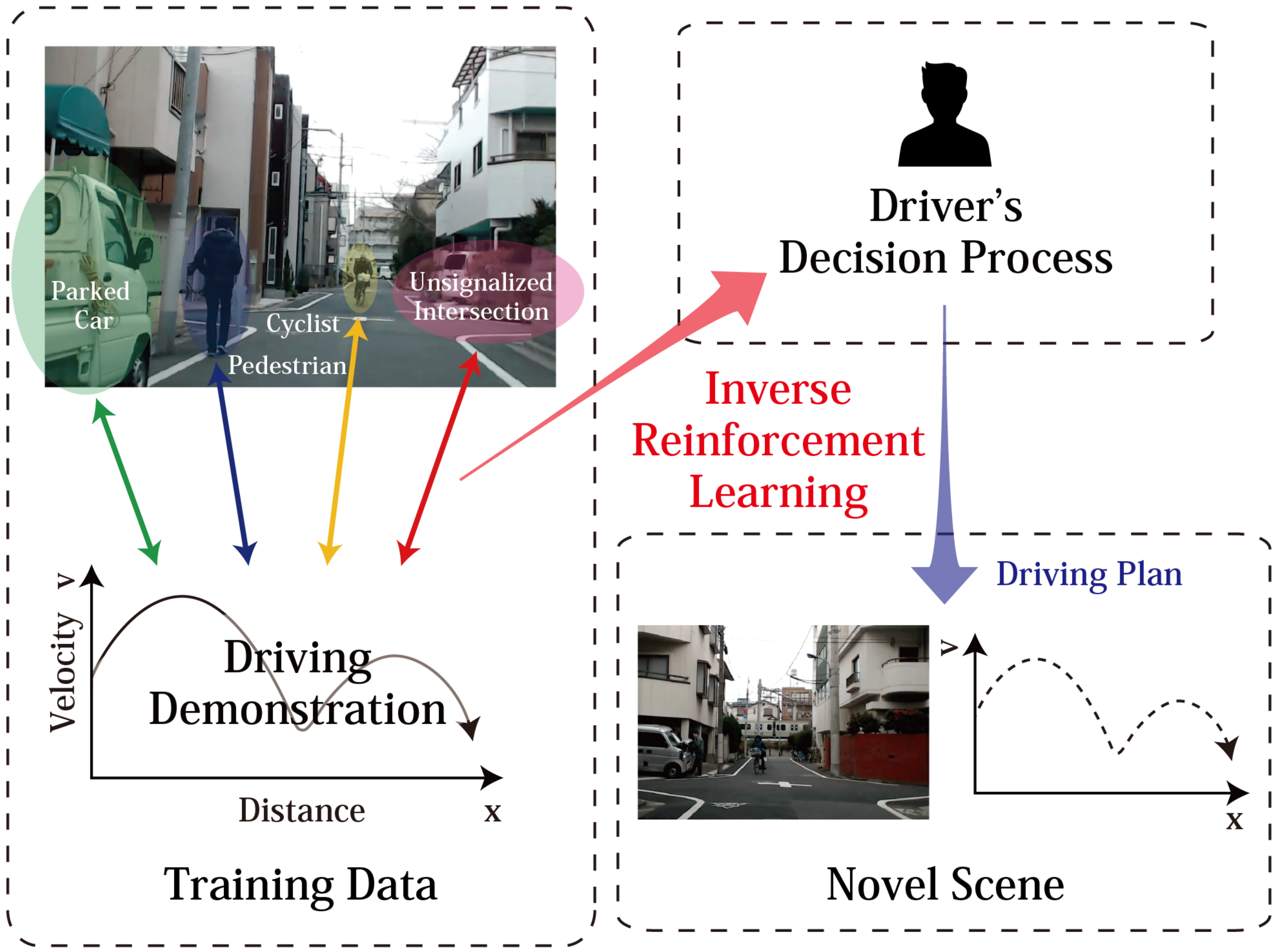
- Defining the reward function that does what you want becomes an art.
- RL algorithms work better with dense rewards than sparse ones. It is tempting to introduce intermediary rewards.
- You end up covering so many special cases that it becomes unusable:
  - Go as fast as you can but not in a curve, except if you are on a closed circuit but not if it rains...

- In the OpenAI **Lego stacking** paper, it was perhaps harder to define the reward function than to implement DDPG.

$$r(b_z^{(1)}, s^P, s^{B1}, s^{B2}) = \begin{cases} 1 & \text{if } \mathrm{stack}(b_z^{(1)}, s^P, s^{B1}, s^{B2}) \\ 0.25 & \text{if } \neg\mathrm{stack}(b_z^{(1)}, s^P, s^{B1}, s^{B2}) \wedge \mathrm{grasp}(b_z^{(1)}, s^P, s^{B1}, s^{B2}) \\ 0.125 & \text{if } \neg(\mathrm{stack}(b_z^{(1)}, s^P, s^{B1}, s^{B2}) \vee \mathrm{grasp}(b_z^{(1)}, s^P, s^{B1}, s^{B2})) \wedge \mathrm{reach}(b_z^{(1)}, s^P, s^{B1}, s^{B2}) \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

Popov, I., Heess, N., Lillicrap, T., Hafner, R., Barth-Maron, G., Vecerik, M., et al. (2017). Data-efficient Deep Reinforcement Learning for Dexterous Manipulation. arXiv:1704.03073.

Inverse Reinforcement Learning



http://www.miubiq.cs.titech.ac.jp/modeling-risk-anticipation-and-defensive-driving-on-residential-roads-using-inverse-reinforcement-learning/

- The goal of **inverse RL** is to learn from **demonstrations** (e.g. from humans) which reward function is maximized.
- This is not **imitation learning**, where you try to learn and reproduce actions.
- The goal if to find a **parametrized representation** of the reward function:

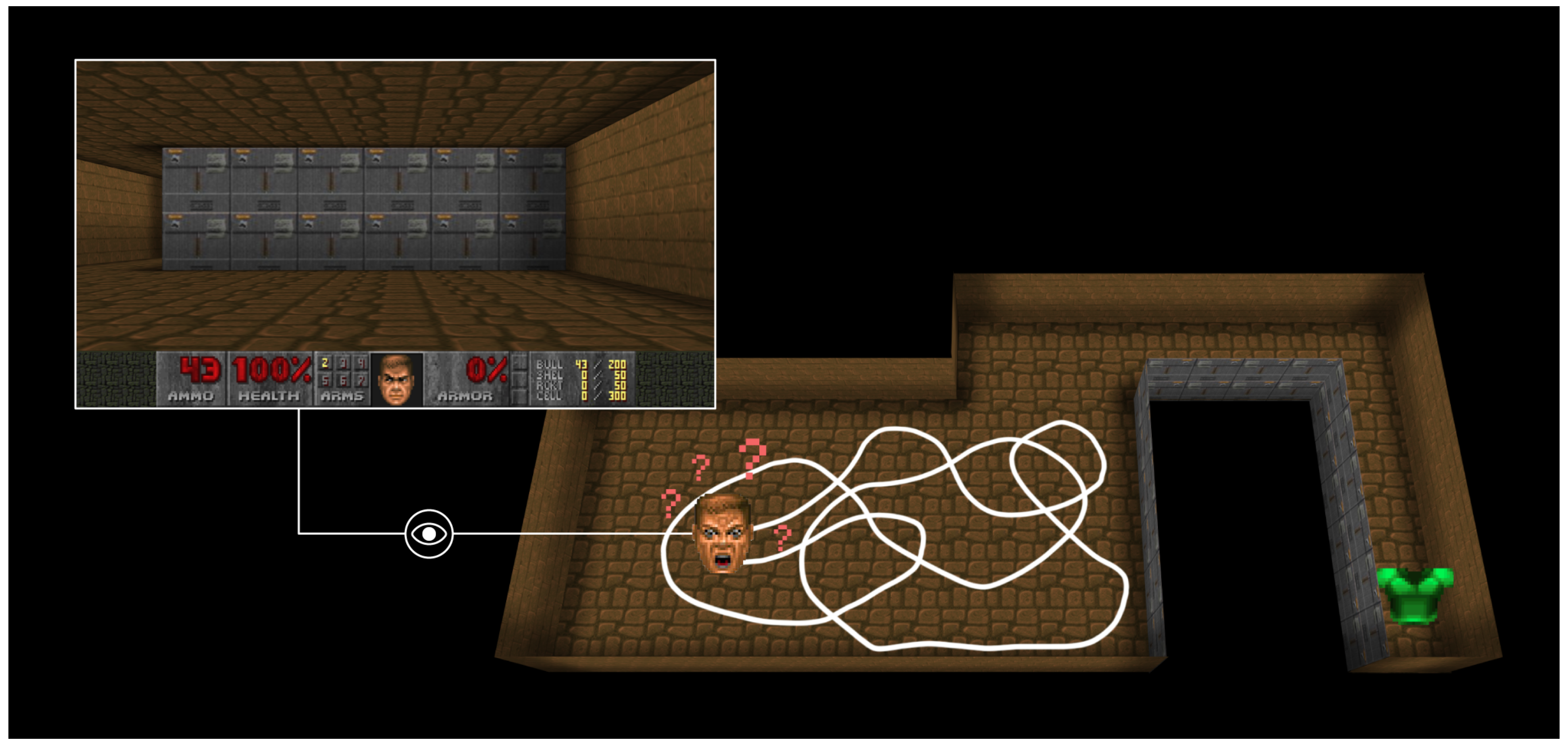
$$\hat{r}(s) = \sum_{i=1}^{K} w_i \, \varphi_i(s)$$

- When the reward function has been learned, you can train a RL algorithm to find the optimal policy.

3 - Intrinsic motivation and curiosity

Intrinsic motivation and curiosity

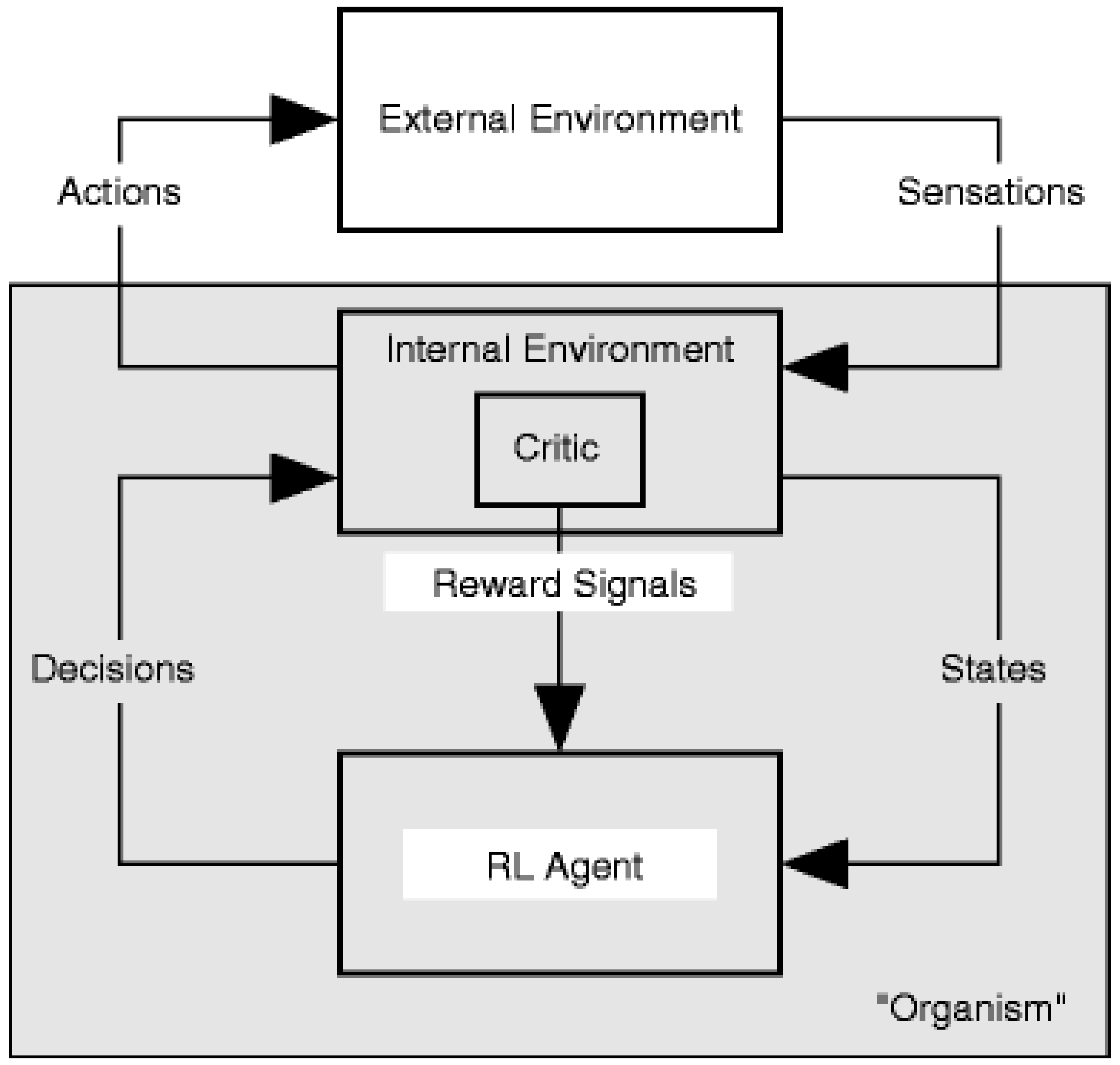
- One fundamental problem of RL is its dependence on the **reward function**.



- When rewards are **sparse**, the agent does not learn much (but see successor representations) unless its random exploration policy makes it discover rewards.
- The reward function is **handmade**, what is difficult in realistic complex problems.

Credit: https://vimeo.com/felixsteger

- Human learning does not (only) rely on maximizing rewards or achieving goals.
- Especially infants discover the world by **playing**, i.e. interacting with the environment out of **curiosity**.
  - What happens if I do that? Oh, that's fun.
- This called **intrinsic motivation**: we are motivated by understanding the world, not only by getting rewards.
- Rewards are internally generated.



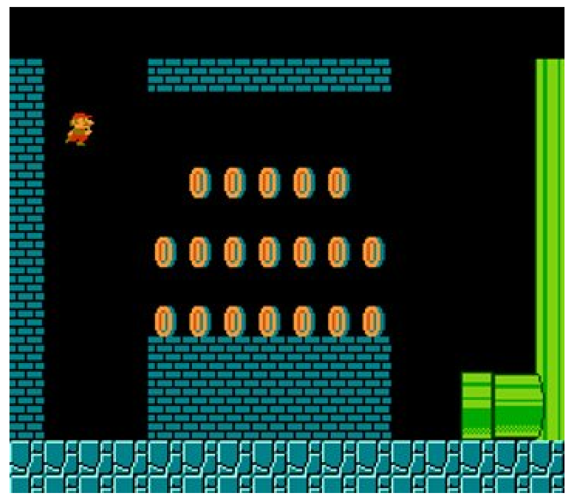
Intrinsic motivation and curiosity

- What is **intrinsically** rewarding / motivating / fun? Mostly what has **unexpected** consequences.
  - If you can predict what is going to happen, it becomes boring.
  - If you cannot predict, you can become **curious** and try to **explore** that action.

Beginning of the game is a **familiar state**

Easy to predict s_{t+1} → **IR will be low**

Found a **new room**



Hard to predict s_{t+1} → **IR will be high**

Source: https://medium.com/data-from-the-trenches/curiosity-driven-learning-through-next-state-prediction-f7f4e2f592fa

- The **intrinsic reward** (IR) of an action is defined as the sensory prediction error:

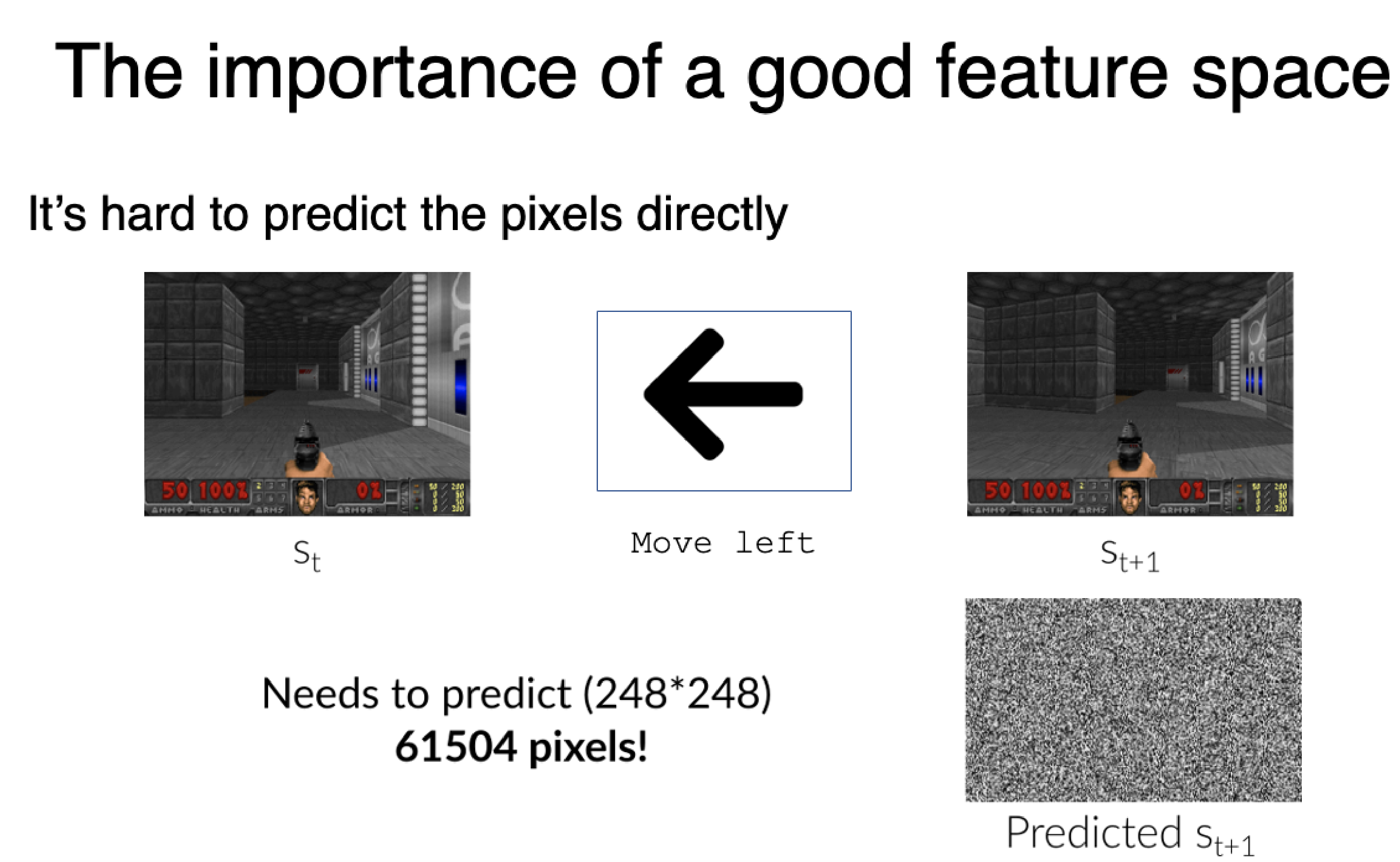
$$\text{IR}(s_t, a_t, s_{t+1}) = ||f(s_t, a_t) - s_{t+1}||$$

where $f(s_t, a_t)$ is a **forward model** predicting the sensory consequences of an action.

- An agent maximizing the IR will tend to visit unknown / poorly predicted states (**exploration**).

Intrinsic motivation and curiosity

- Is it a good idea to predict frames directly?
- Frames are highly dimensional and there will always be a remaining error.



Source: https://medium.com/data-from-the-trenches/curiosity-driven-learning-through-next-state-prediction-f7f4e2f592fa

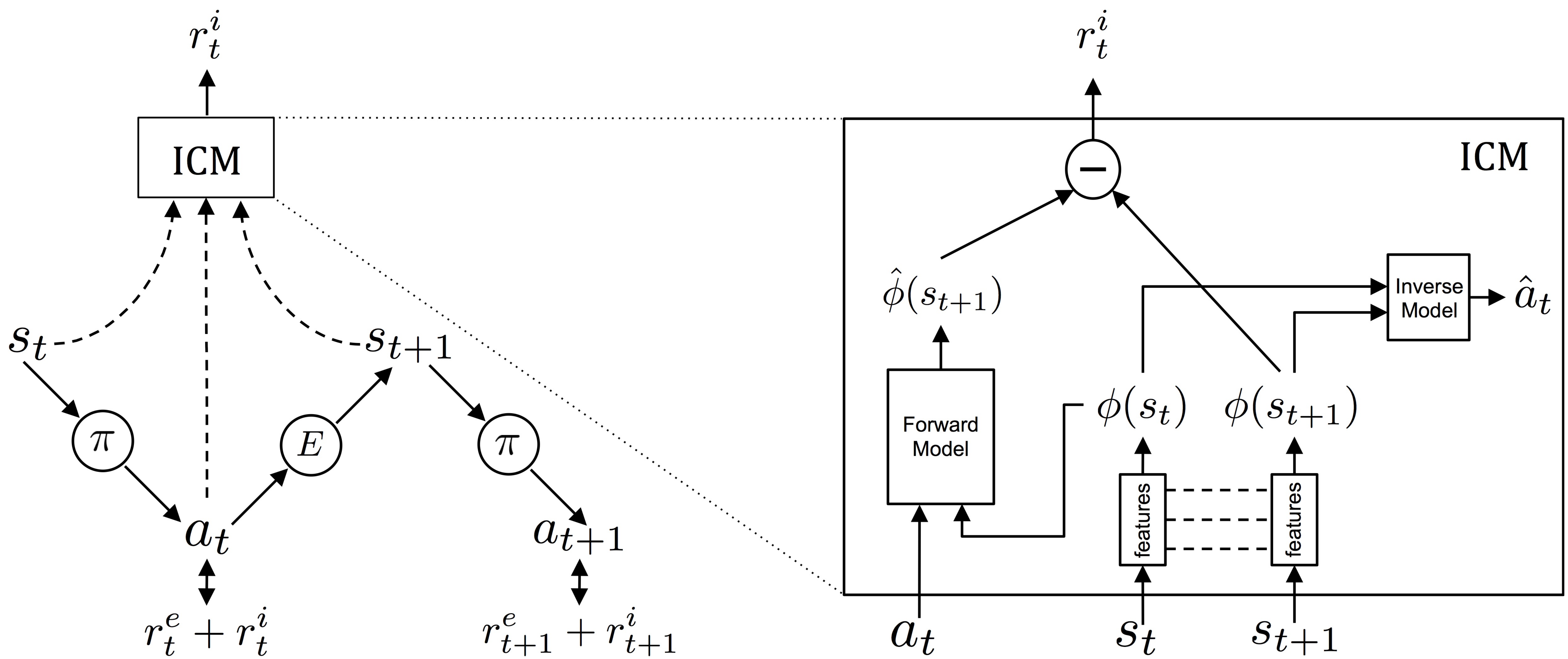
- What can we do? As usual, predict in a latent space!

- Moreover, they can be noisy and unpredictable, without being particularly interesting.

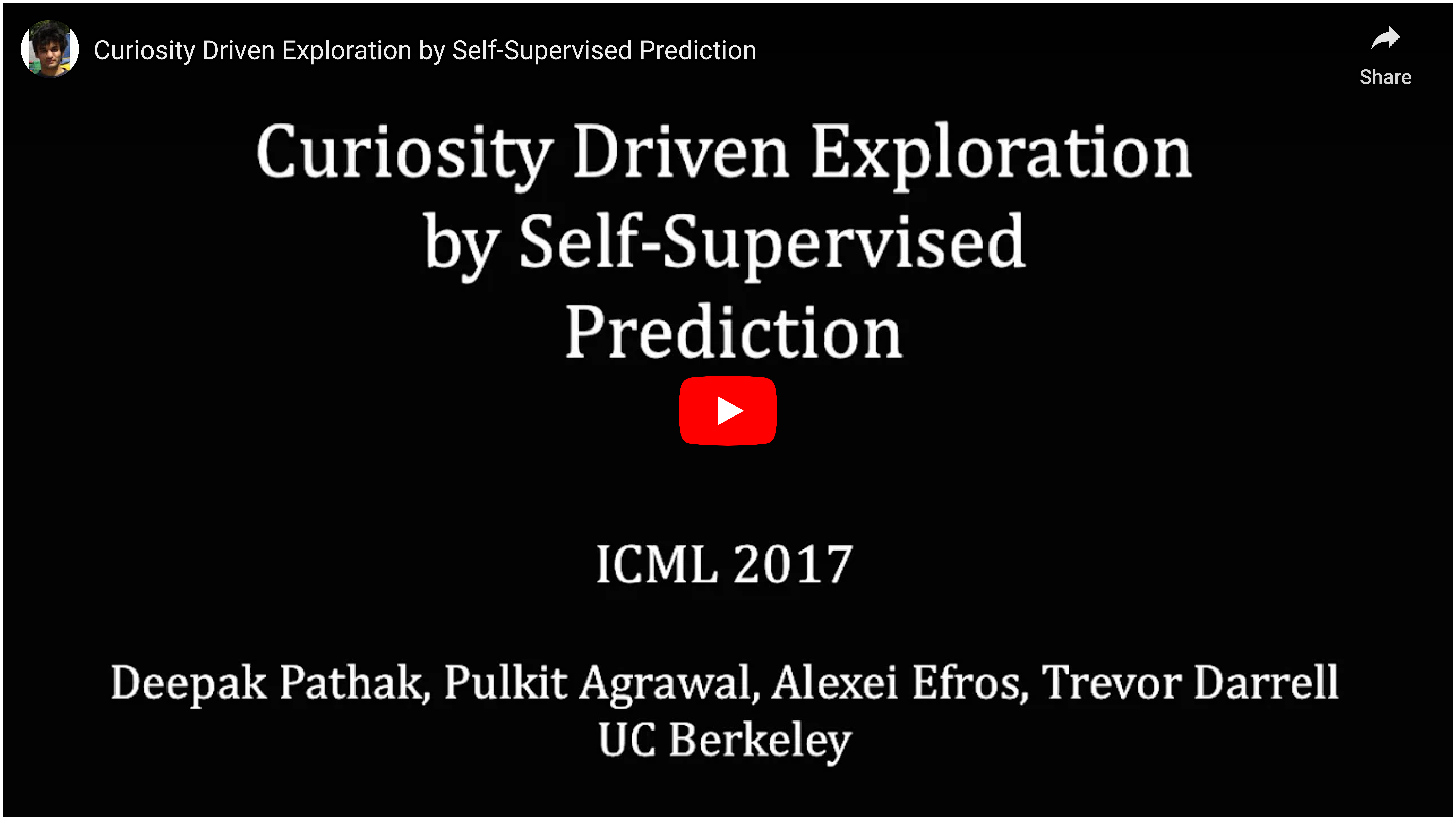
Source: Giphy

Intrinsic curiosity module (ICM)

- The intrinsic curiosity module (ICM) learns to provide an intrinsic reward for a transition (s_t, a_t, s_{t+1}) by comparing the predicted latent representation $\hat{\phi}(s_{t+1})$ (using a **forward** model) to its “true” latent representation $\phi(s_{t+1})$.
- The feature representation $\phi(s_t)$ is trained using an **inverse model** predicting the action leading from s_t to s_{t+1}.

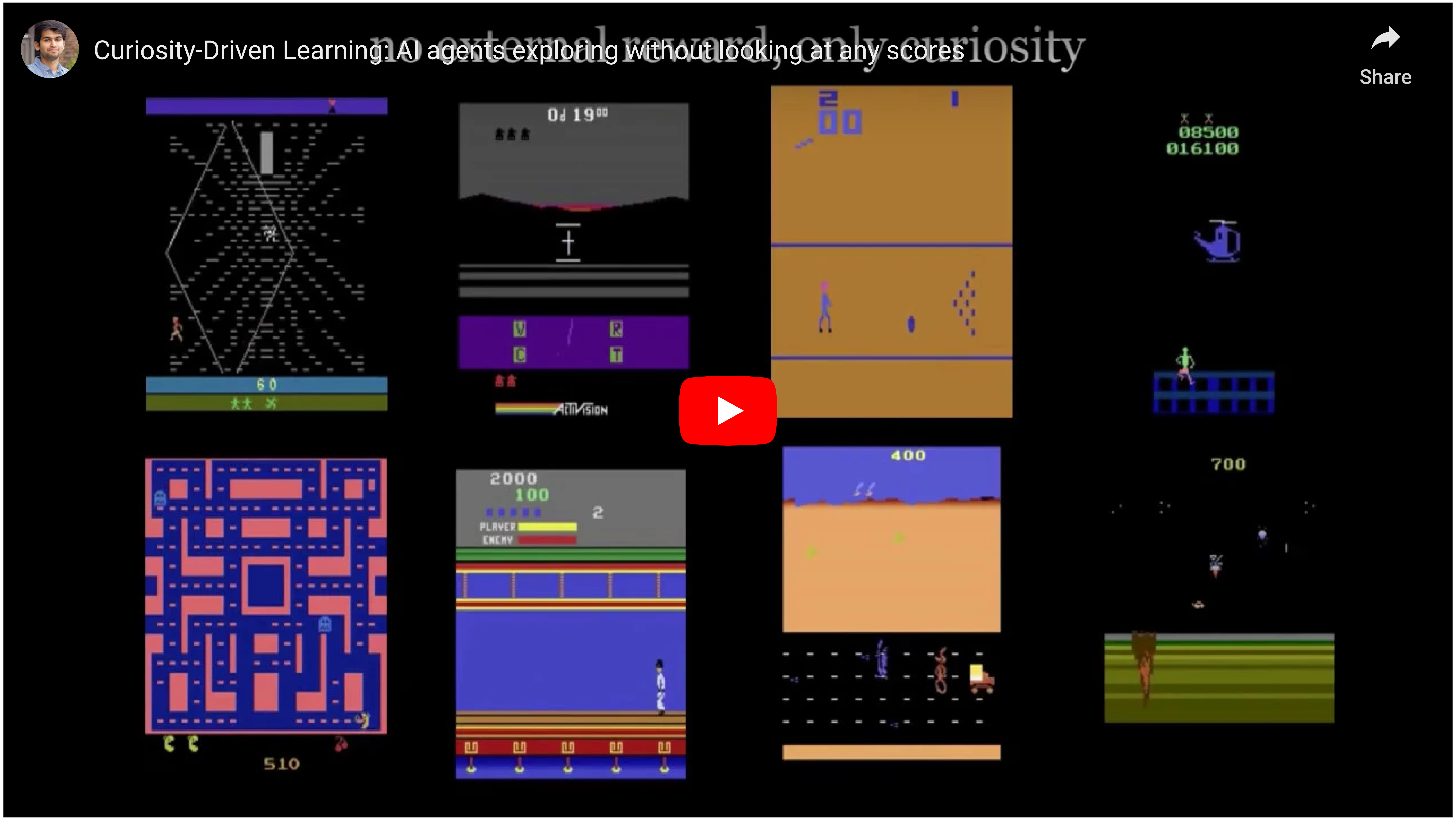


Intrinsic motivation and curiosity



Pathak D, Agrawal P, Efros AA, Darrell T. (2017). Curiosity-driven Exploration by Self-supervised Prediction. arXiv:170505363.

Intrinsic motivation and curiosity



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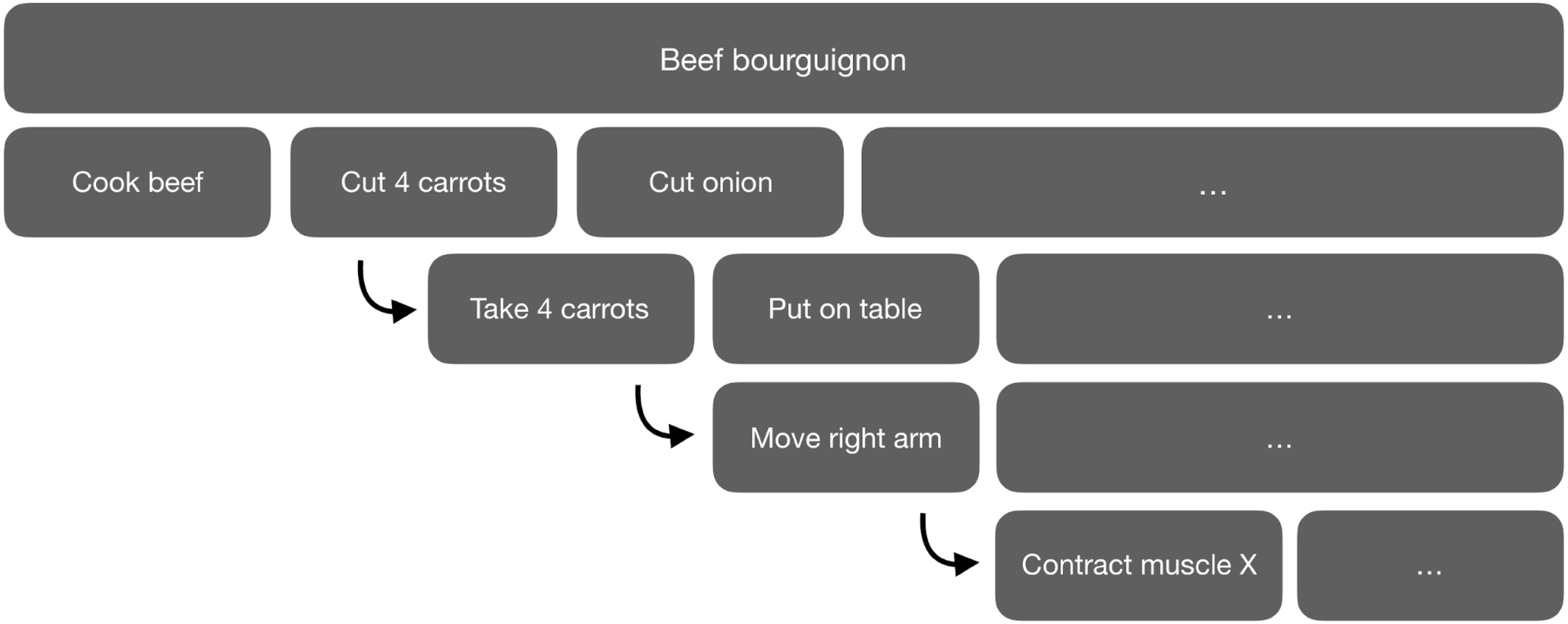
4 - Hierarchical RL - learning different action levels

Hierarchical RL - learning different action levels

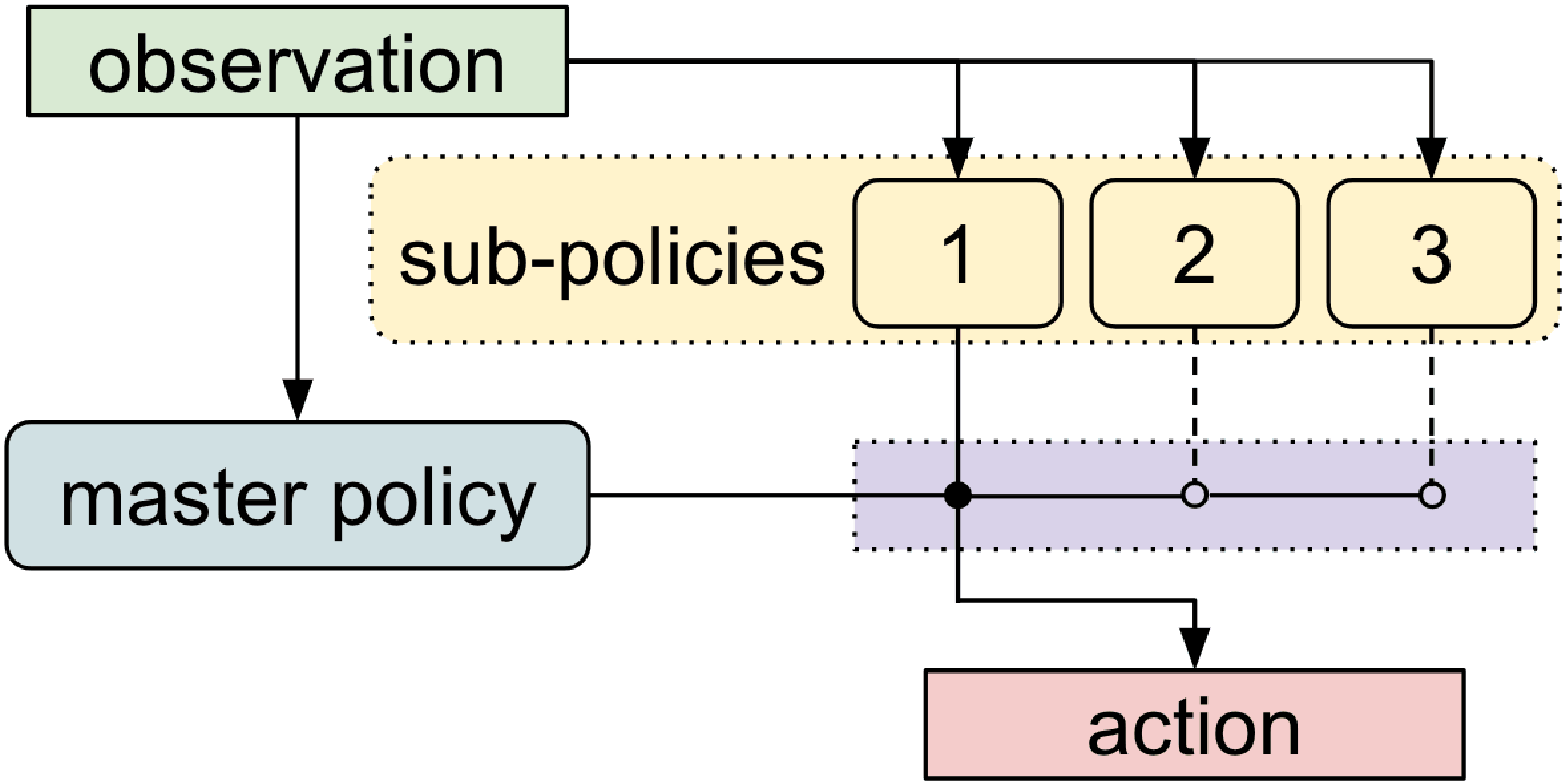
- In all previous RL methods, the action space is fixed.
- When you read a recipe, the actions are “Cut carrots”, “Boil water”, etc.
- But how do you perform these **high-level actions**? Break them into subtasks iteratively until you arrive to muscle activations.
- But it is not possible to learn to cook a boeuf bourguignon using muscle activations as actions.



Source: https://thegradient.pub/the-promise-of-hierarchical-reinforcement-learning/

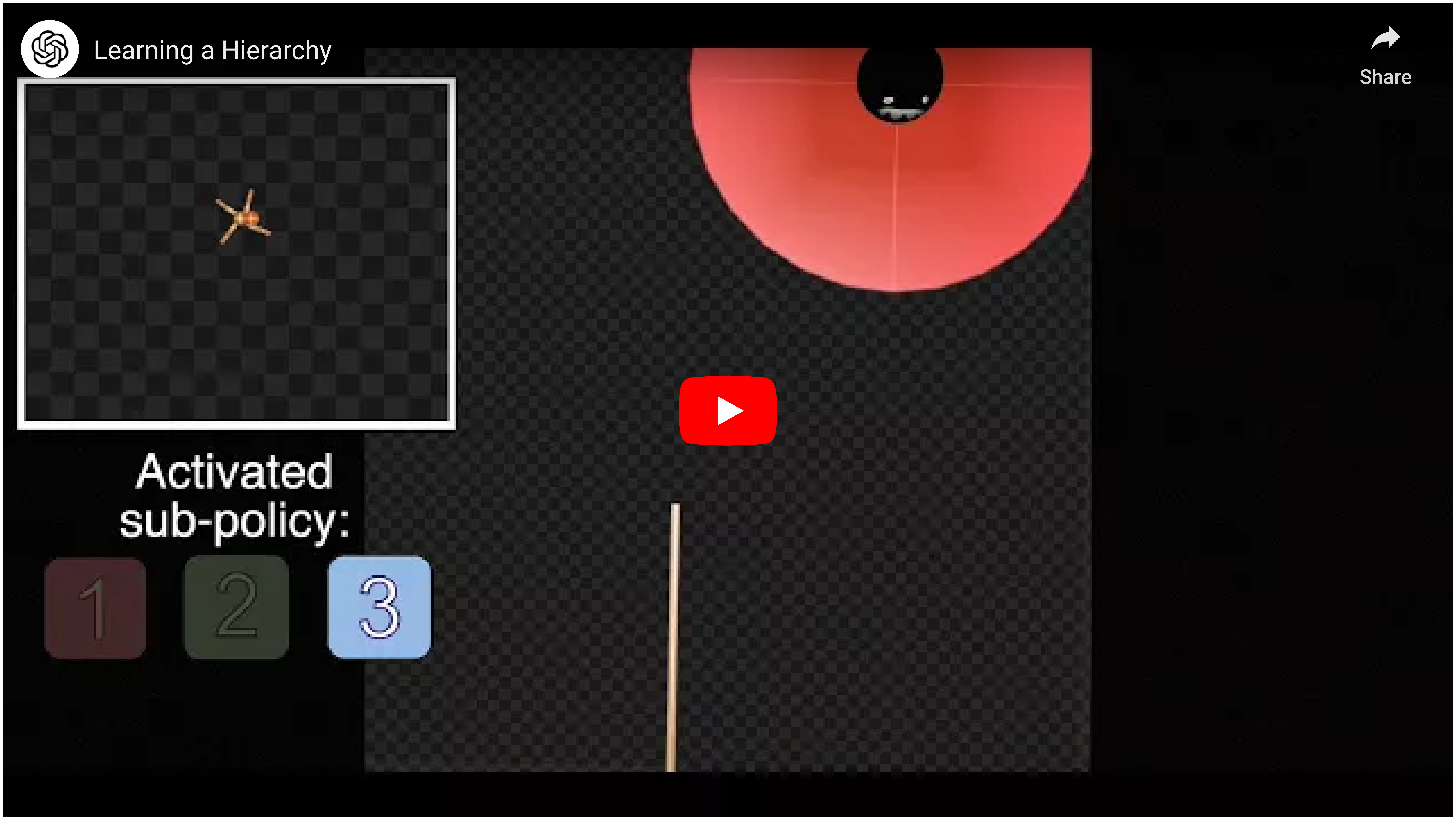
Meta-Learning Shared Hierarchies

- Sub-policies (**options**) can be trained to solve simple tasks (going left, right, etc).
- A **meta-learner** or controller then learns to call each sub-policy when needed, at a much lower frequency.

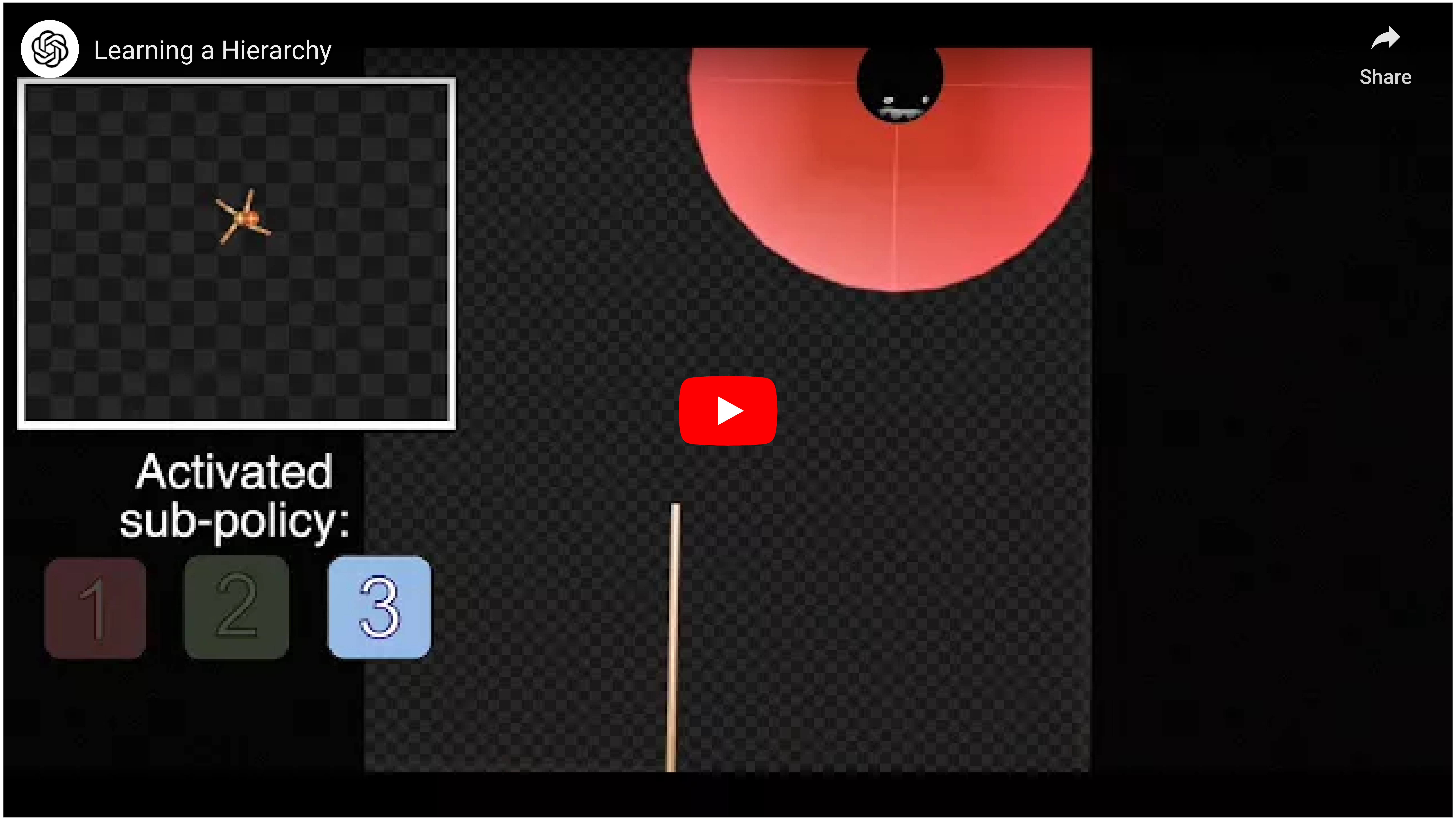


Frans, K., Ho, J., Chen, X., Abbeel, P., and Schulman, J. (2017). Meta Learning Shared Hierarchies. arXiv:1710.09767

Meta-Learning Shared Hierarchies



Meta-Learning Shared Hierarchies



https://openai.com/blog/learning-a-hierarchy/

Hierarchical Reinforcement Learning

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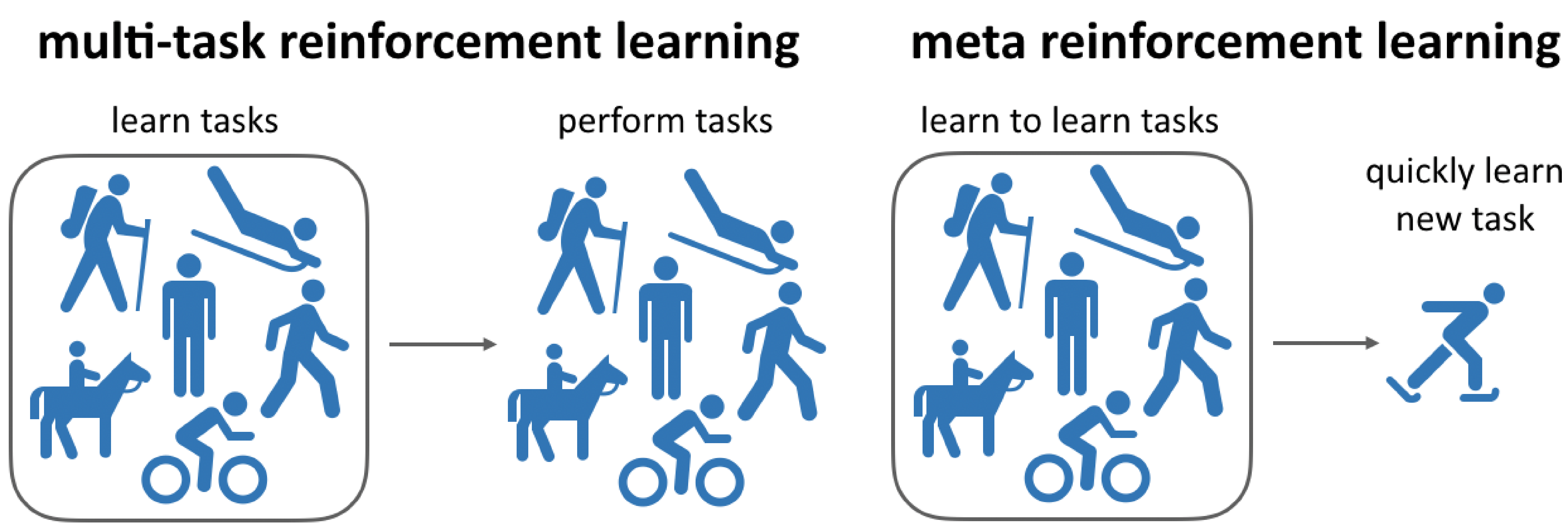
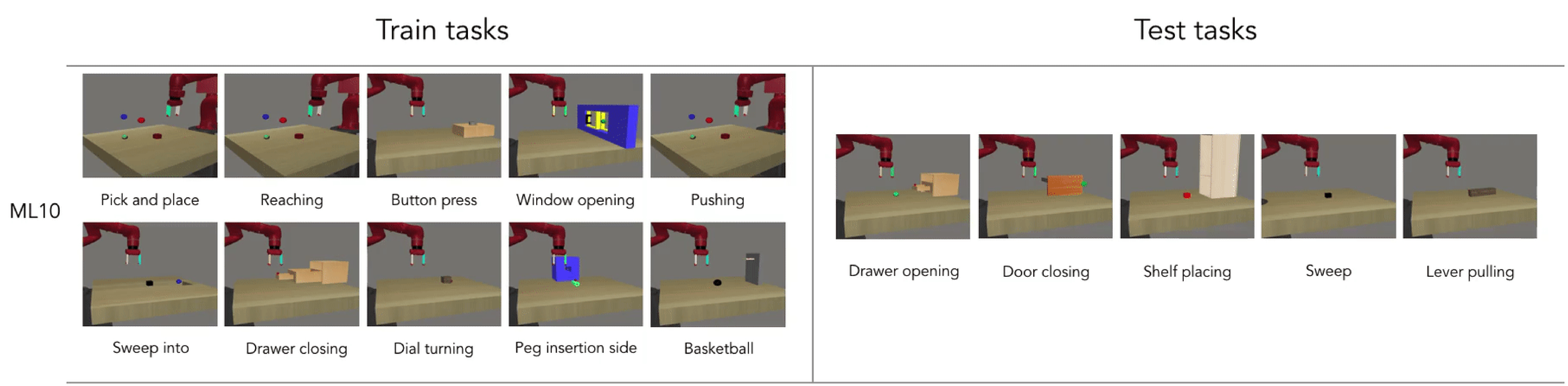
- **Spinal-cortical:** Heess, N., Wayne, G., Tassa, Y., Lillicrap, T., Riedmiller, M., and Silver, D. (2016). Learning and Transfer of Modulated Locomotor Controllers. arXiv:1610.05182.

5 - Meta Reinforcement learning - RL^2

Meta RL: Learning to learn

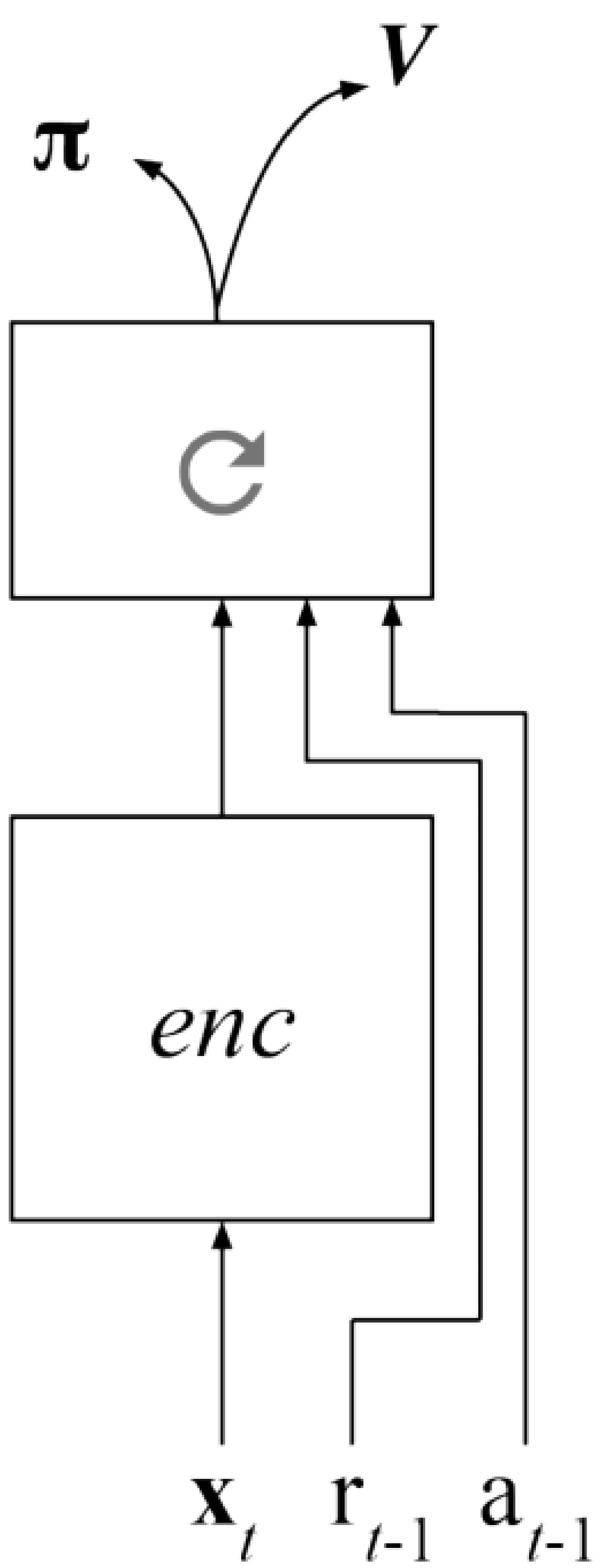
- **Meta learning** is the ability to reuse skills acquired on a set of tasks to quickly acquire new (similar) ones (generalization).



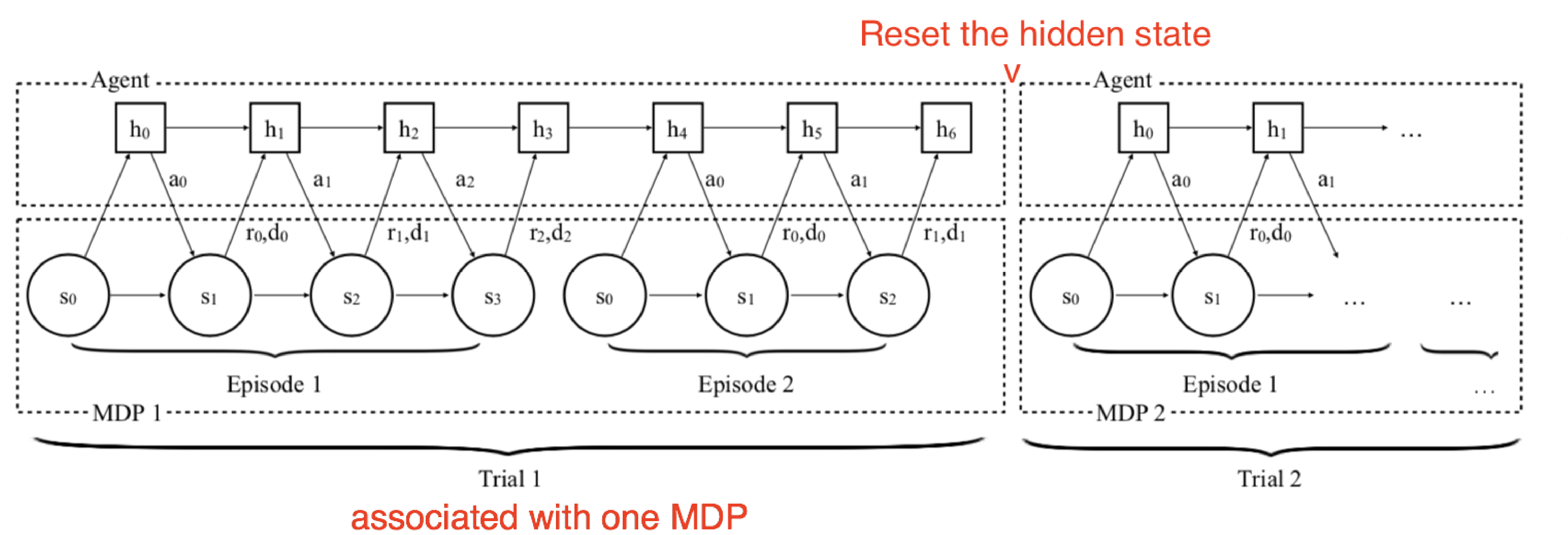


Source: https://meta-world.github.io/

Meta RL: Learning to learn

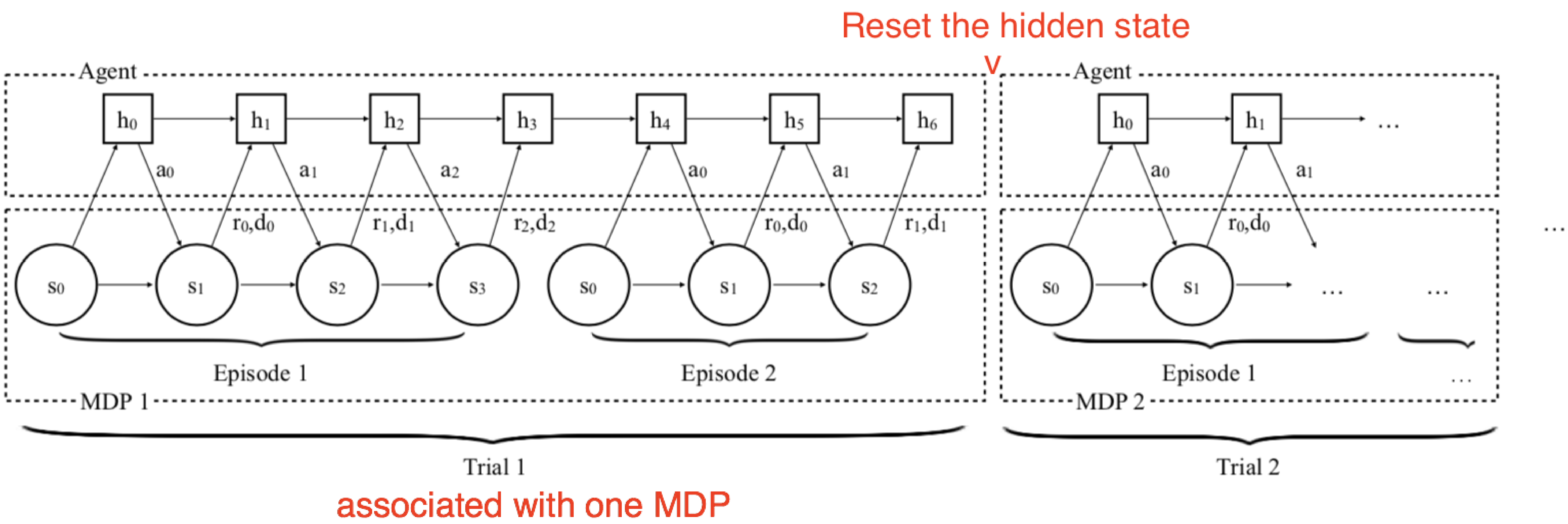


- Meta RL is based on the idea of **fast and slow** learning:
  - Slow learning is the adaptation of weights in the NN.
  - Fast learning is the adaptation to changes in the environment.
- A simple strategy developed concurrently by (Wang et al. 2016) and (Duan et al. 2016) is to have a model-free algorithm (e.g. A3C) integrate with a LSTM layer not only the current state s_t, but also the previous action a_{t-1} and reward r_t.
- The policy of the agent becomes **memory-guided**: it selects an action depending on what it did before, not only the state.



Wang et al.. (2016). Learning to reinforcement learn. arXiv:161105763.

Meta RL: Learning to learn

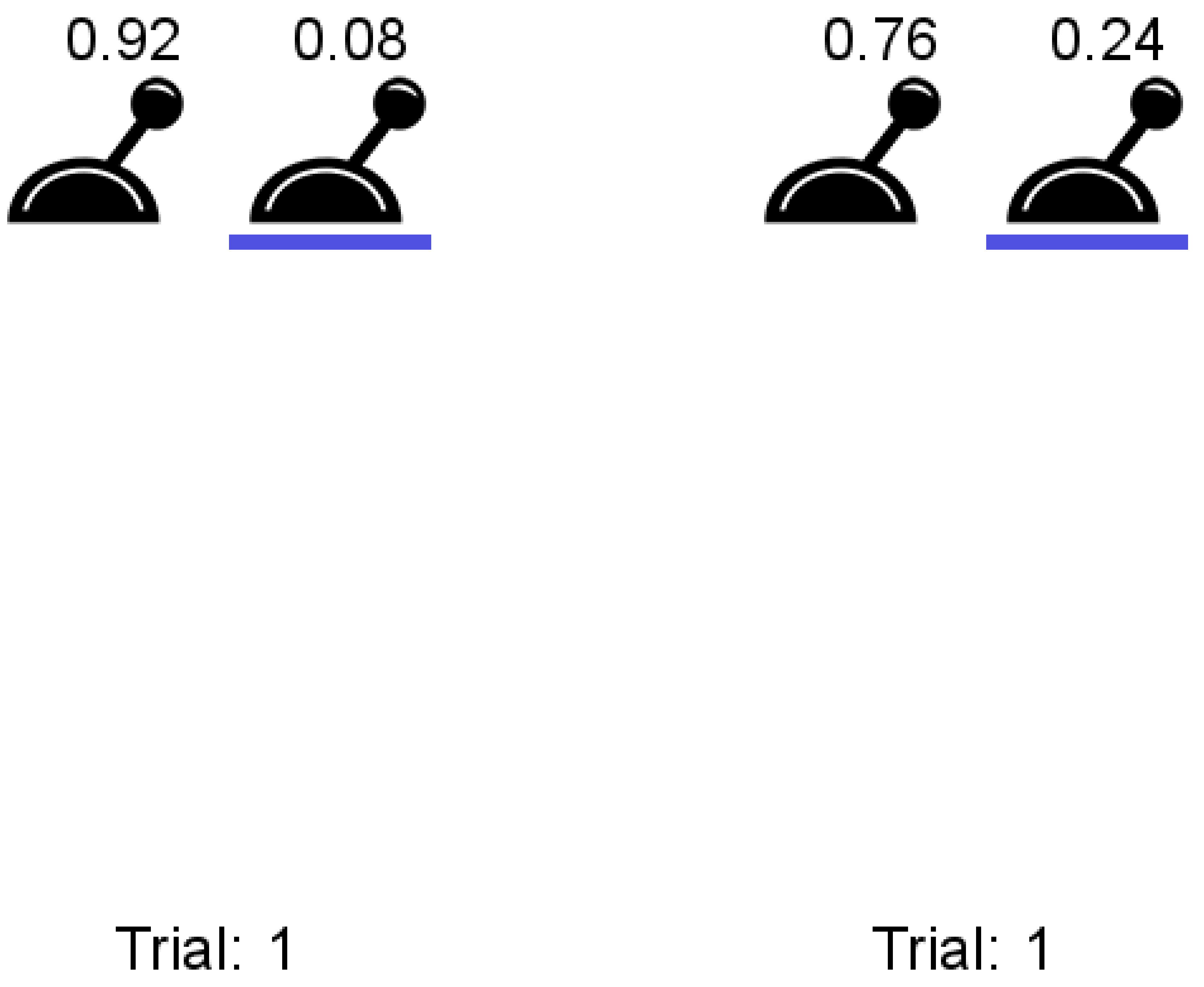


- The algorithm is trained on a set of similar MDPs:
    1. Select a MDP $\mathcal{M}$.
    2. Reset the internal state of the LSTM.
    3. Sample trajectories and adapt the weights.
    4. Repeat 1, 2 and 3.

Duan Y, Schulman J, Chen X, Bartlett PL, Sutskever I, Abbeel P. (2016). RL^2: Fast Reinforcement Learning via Slow Reinforcement Learning. arXiv:161102779.

Meta RL: Learning to learn

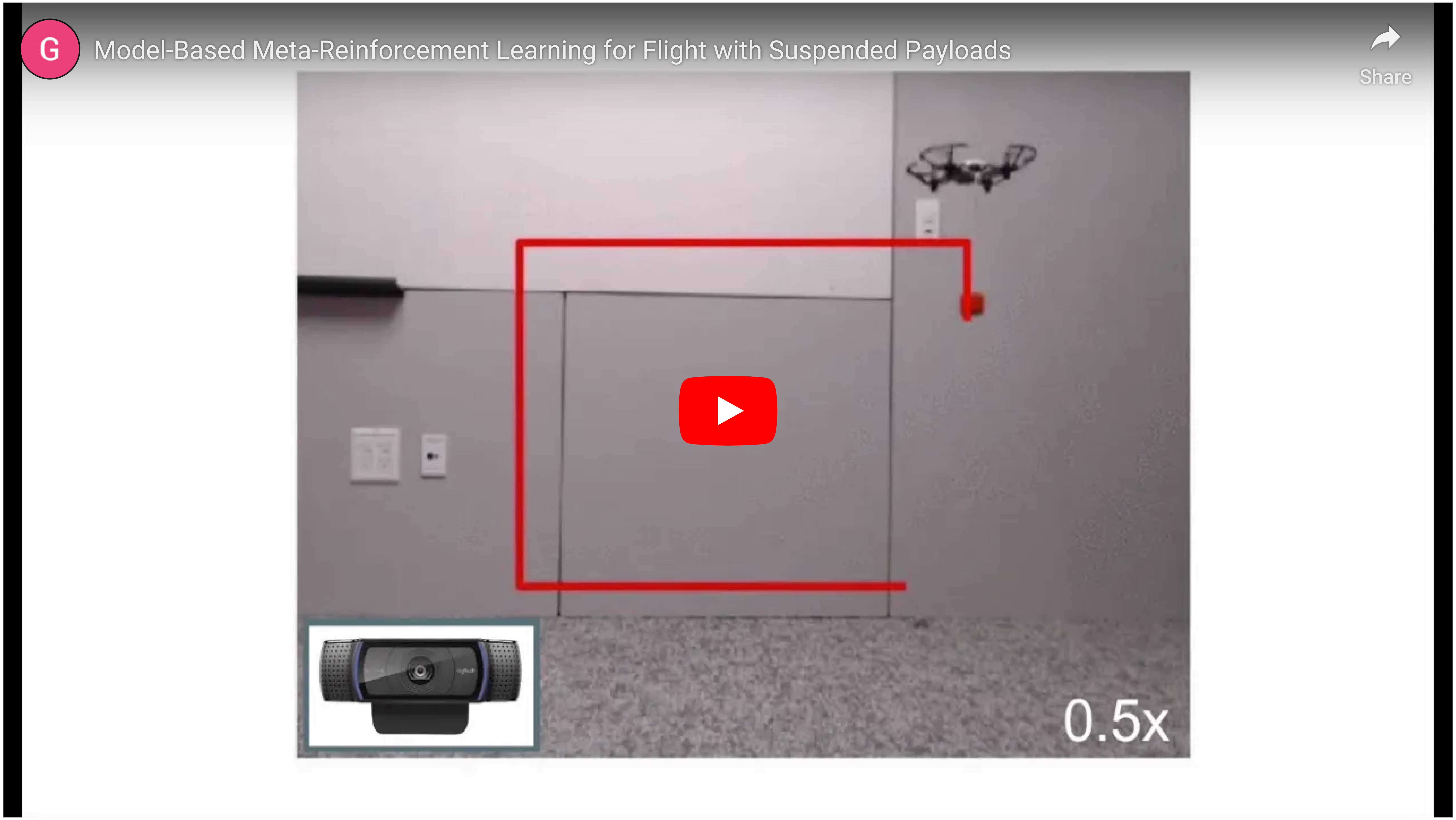
- The meta RL can be be trained an a multitude of 2-armed bandits, each giving a reward of 1 with probability p and $1 - p$.
- Left is a classical bandit algorithm, right is the meta bandit:



Source: https://hackernoon.com/learning-policies-for-learning-policies-meta-reinforcement-learning-rl%C2%B2-in-tensorflow-b15b592a2ddf

- The meta bandit has learned that the best strategy for any 2-armed bandit is to sample both actions randomly at the beginning and then stick to the best one.
- The meta bandit does not learn to solve each problem, it learns **how** to solve them.

Model-Based Meta-Reinforcement Learning for Flight with Suspended Payloads



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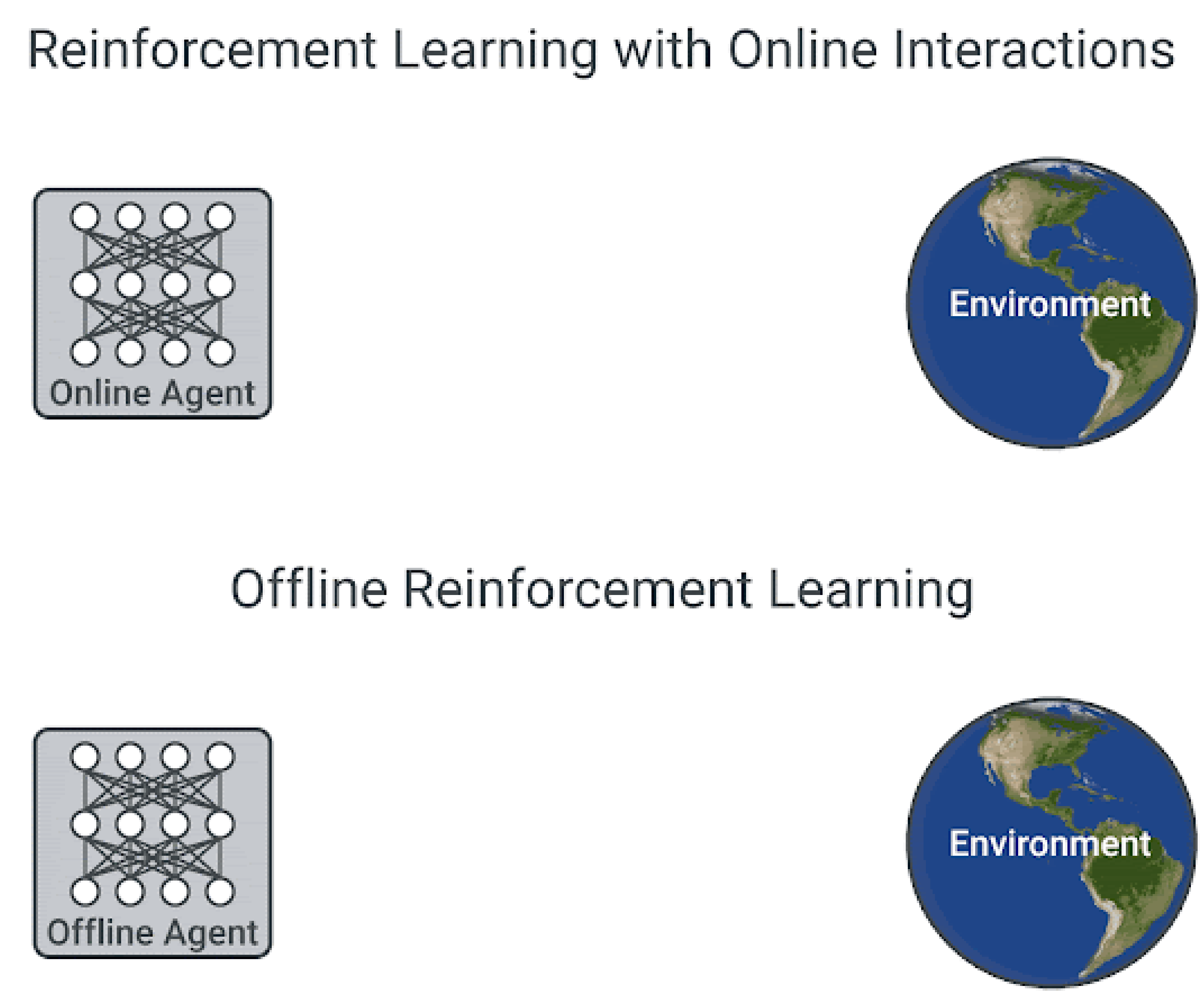
6 - Offline RL

Offline RL

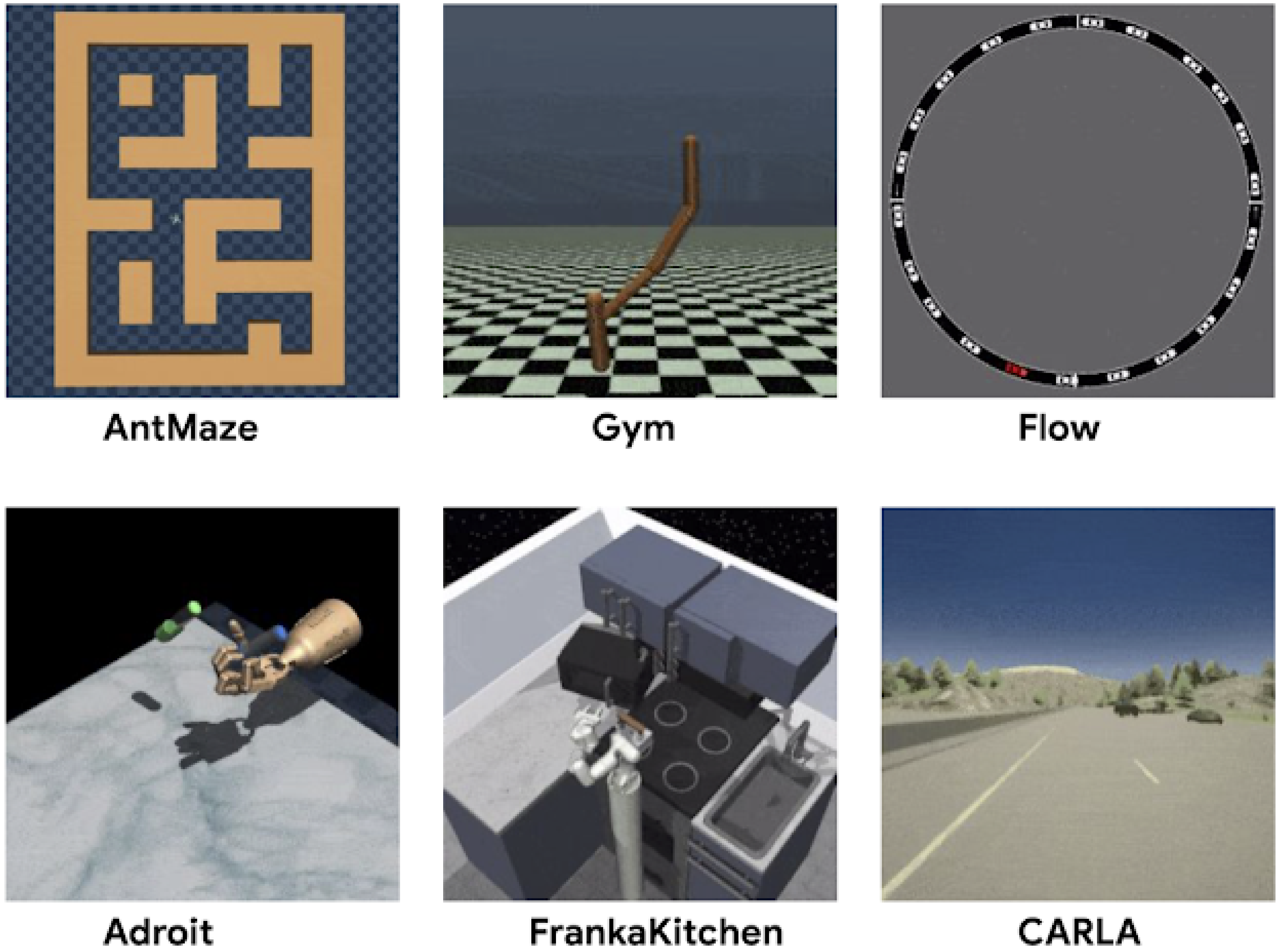
- Even off-policy algorithms need to interact with the environment: the behavior policy is ϵ-soft around the learned policy.
- Is it possible to learn purely **offline** from recorded transitions using another policy (experts)? Data efficiency.
- This would bring safety: the agent would not explore dangerous actions.



Source: https://ai.googleblog.com/2020/04/an-optimistic-perspective-on-offline.html

D4RL

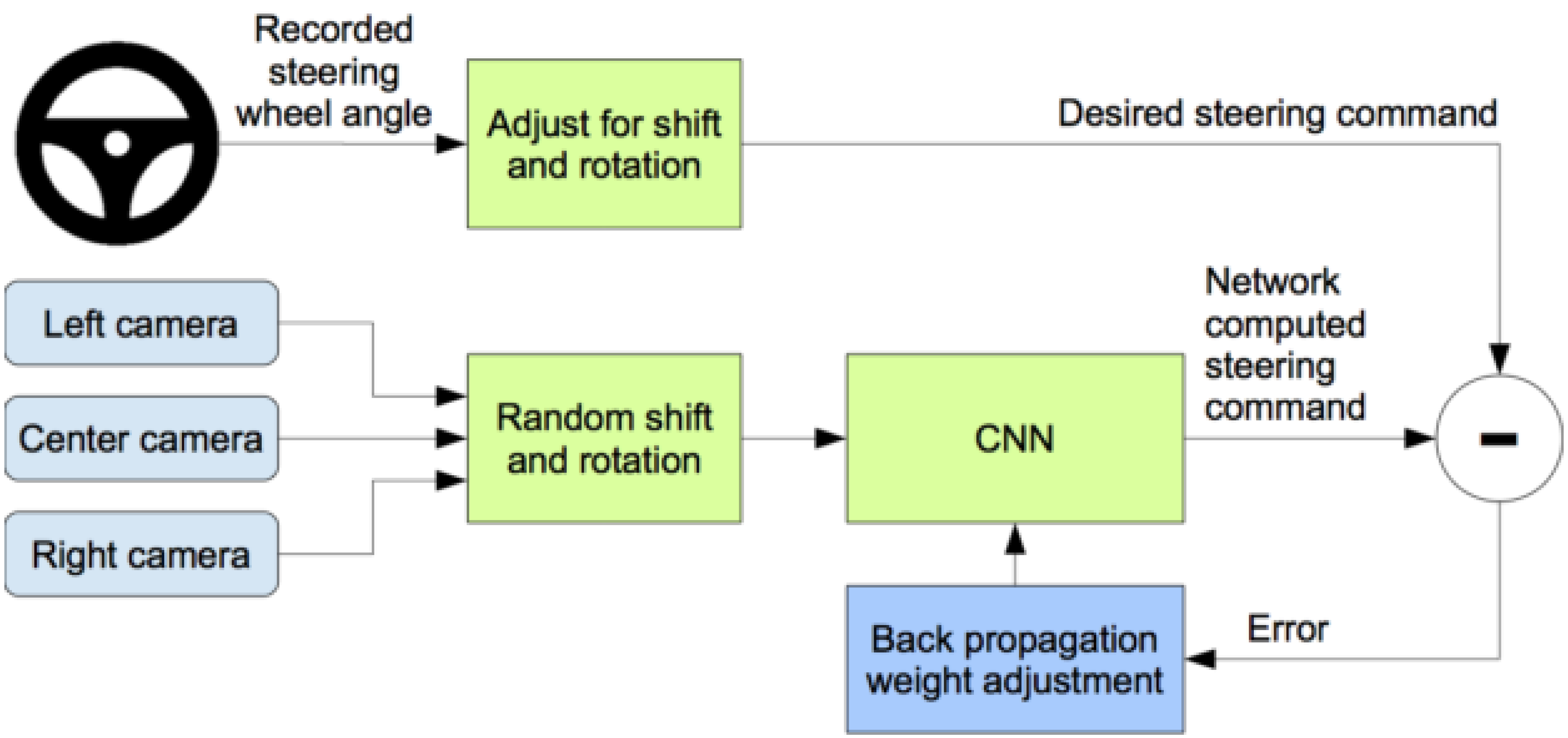
- D4RL (https://sites.google.com/view/d4rl/home) provides offline data recorded using expert policies to test offline algorithms.



https://ai.googleblog.com/2020/08/tackling-open-challenges-in-offline.html

Behavioral cloning

- As no exploration is allowed, the model is limited by the quality of the data: if the acquisition policy is random, there is not much to hope.
- If we have already a good policy, but slow or expensive to compute, we could try to transfer it to a fast neural network.
- If the policy is a human expert, it is called **learning from demonstrations** (lfd) or **imitation learning**.
- The simplest approach to offline RL is **behavioral cloning**: simply supervised learning of (s, a) pairs…

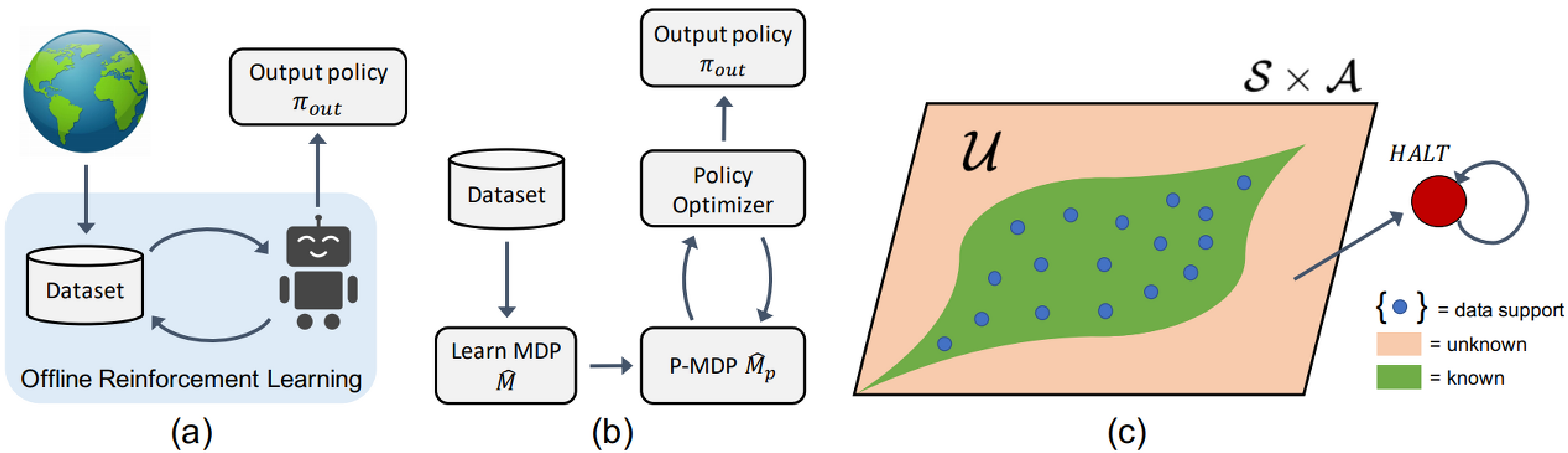


M Bojarski, D Del Testa, D Dworakowski, B Firner (2016). End to end learning for self-driving cars. arXiv:1604.07316

Dave2 : NVIDIA's self-driving car

Distribution shift

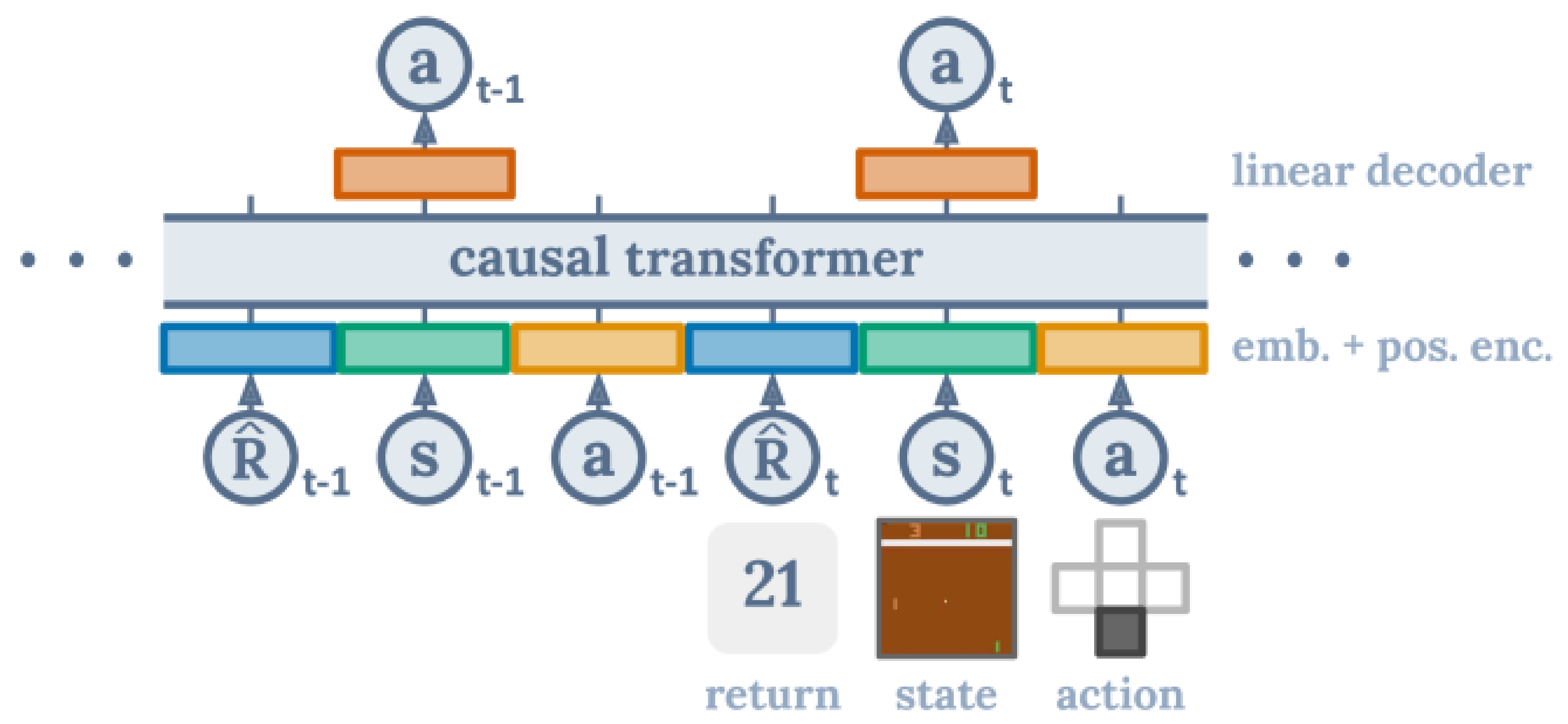
- The main problem in offline RL is the **distribution shift**: what if the trained policy assigns a non-zero probability to a (s, a) pair that is **outside** the training data?
- Most offline RL methods are **conservative** methods, which try to learn policies staying close to the known distribution of the data. Examples:
  - Batch-Contrained deep Q-learning (model-free), MOREL (model-based)...

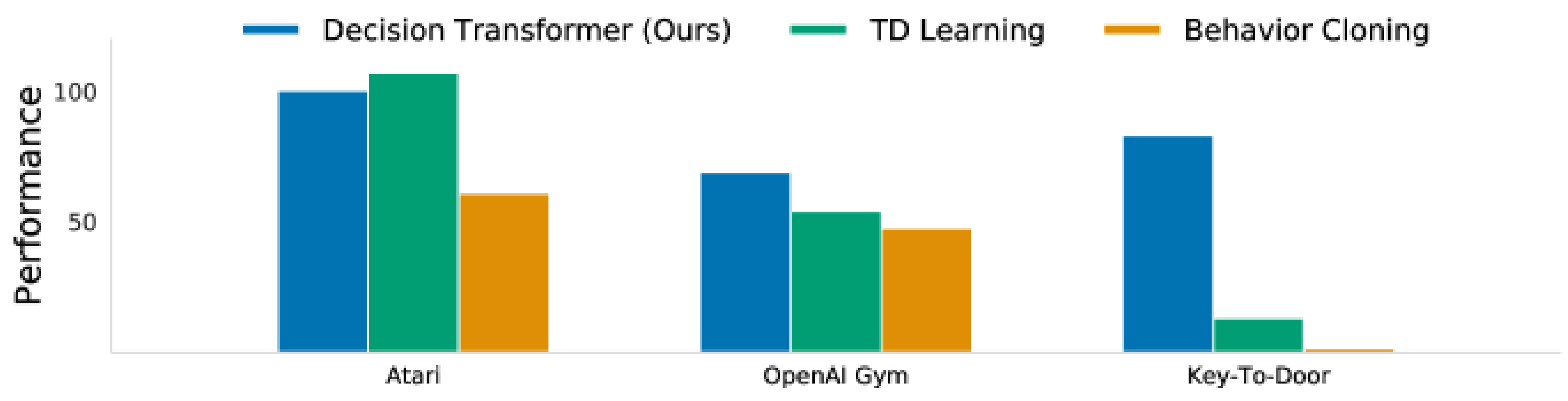


Source: https://kenshinhm.tistory.com/37

Decision transformer

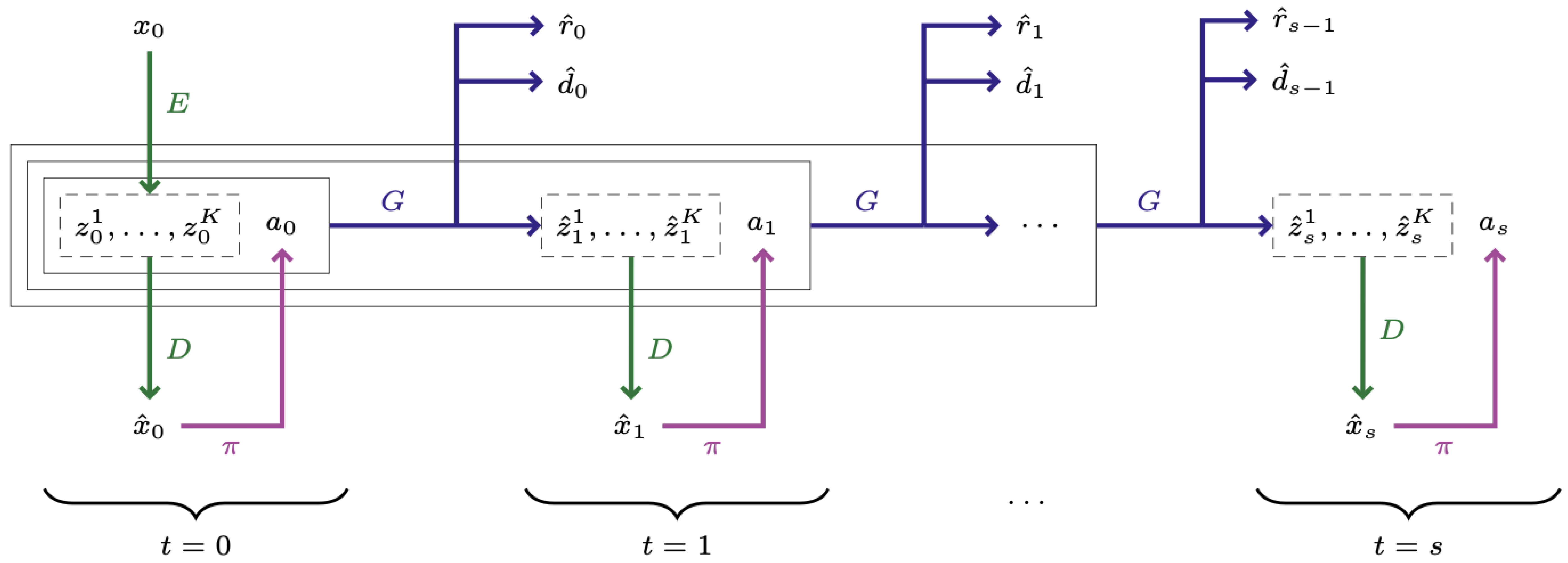
- Transformers are the new SotA method to transform sequences into sequences.
- Why not sequences of states into sequences of actions?
- The **decision transformer** takes complete offline trajectories as inputs (s, a, r, s…) and predicts autoregressively the next action.

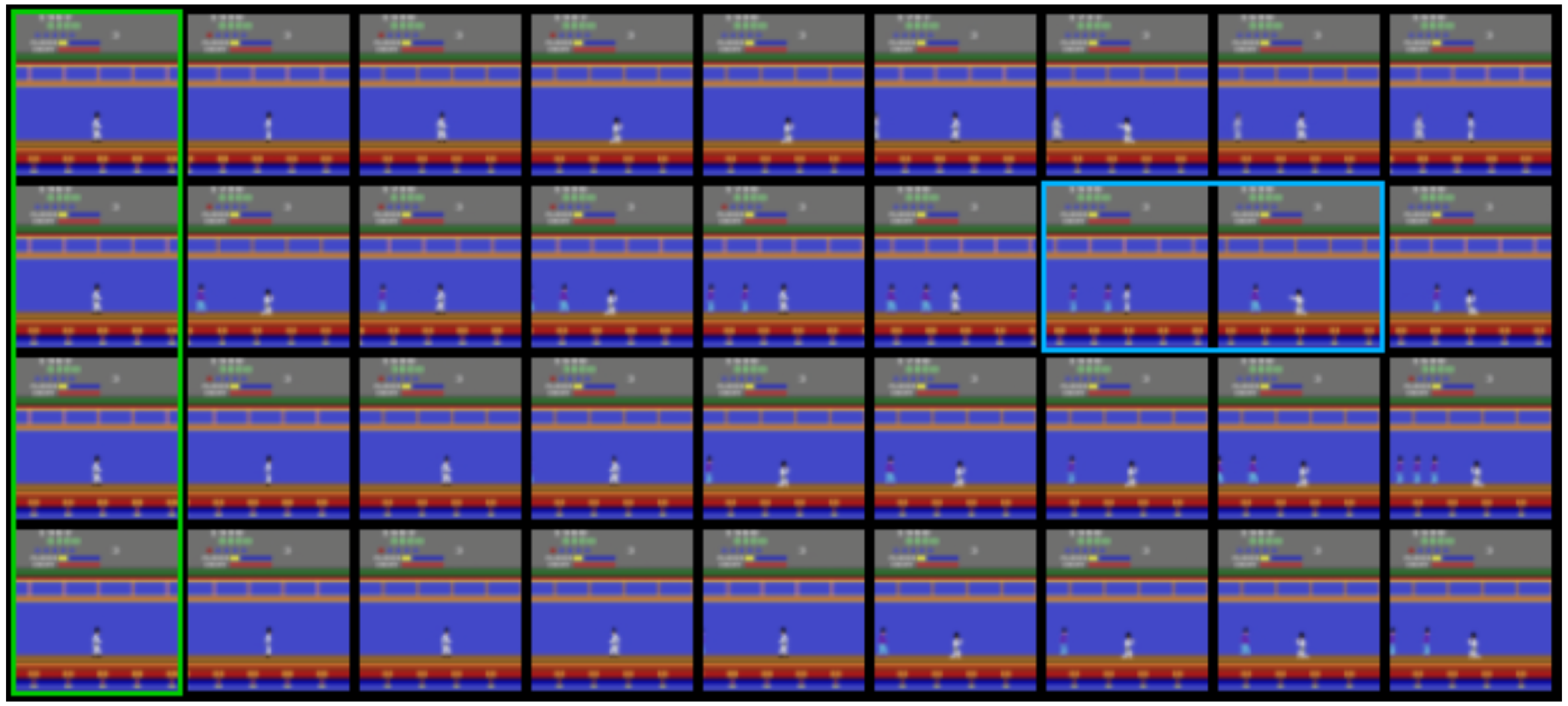




Source: https://arxiv.org/abs/2106.01345

Transformers as World models





Micheli, V., Alonso, E., & Fleuret, F. (2022). Transformers are Sample Efficient World Models (arXiv:2209.00588). https://doi.org/10.48550/arXiv.2209.00588

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