UNIVERSITY OF TECHNOLOGY
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CHEMNITZ

Deep Reinforcement Learning

Learned world models

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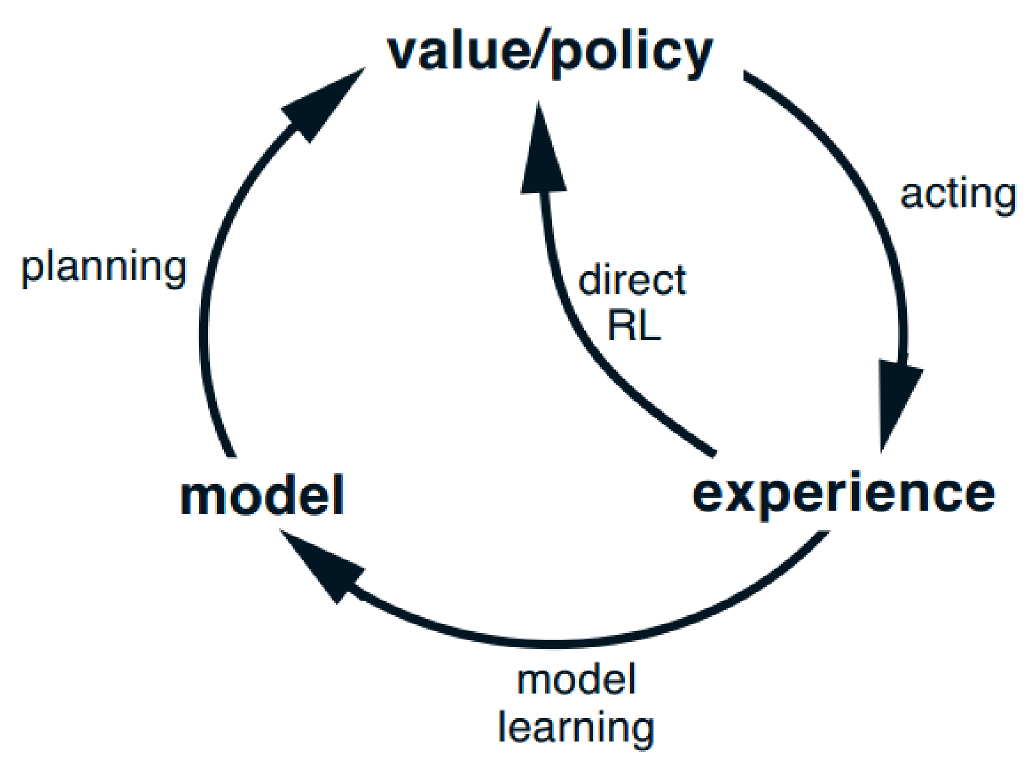
Model-based RL algorithms with learned models

Model-based augmented model-free (MBMF)

- Dyna-Q: the model **generates** imaginary transitions/rollouts that are used to train a MF algorithm.

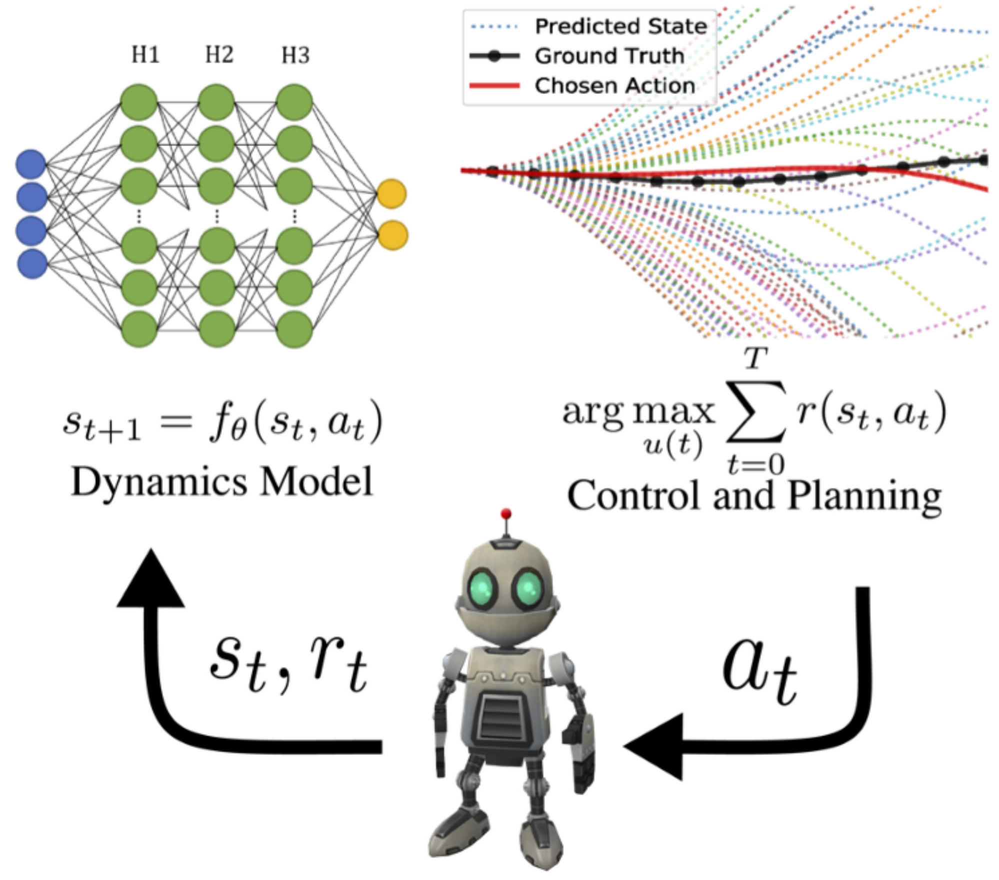


Source: Sutton and Barto (1998)

- NAF: Normalized advantage functions (Gu et al., 2016)
- I2A: Imagination-augmented agents (Weber et al., 2017)
- MBVE: model-based value estimation (Feinberg et al., 2018)

Model-based planning

- MPC: the learned model is used to **plan** actions that maximize the RL objective.



Source: https://arxiv.org/abs/1901.03737

- TDM: Temporal difference models (Pong et al., 2018)
- World models (Ha and Schmidhuber, 2018)
- PlaNet (Hafner et al., 2019)
- Dreamer (Hafner et al., 2020)

1 - I2A - Imagination-augmented agents

Imagination-Augmented Agents for Deep Reinforcement Learning

Théophane Weber*   Sébastien Racanière*   David P. Reichert*   Lars Buesing
Arthur Guez   Danilo Rezende   Adria Puigdomènech Badia   Oriol Vinyals
Nicolas Heess   Yujia Li   Razvan Pascanu   Peter Battaglia
Demis Hassabis   David Silver   Daan Wierstra
DeepMind

https://deepmind.com/blog/article/agents-imagine-and-plan

I2A - Imagination-augmented agents

- I2A is a **model-based augmented model-free method**: it trains a MF algorithm (A3C) with the help of **rollouts** generated by a MB model.

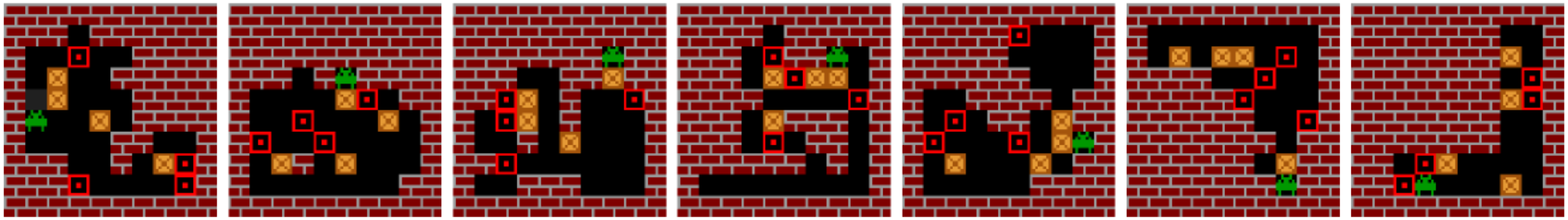


Figure 3: *Random examples of procedurally generated Sokoban levels.* The player (green sprite) needs to push all 4 boxes onto the red target squares to solve a level, while avoiding irreversible mistakes. Our agents receive sprite graphics (shown above) as observations.

- They showcase their algorithm on the puzzle environment **Sokoban**, where you need to move boxes to specified locations.
- Sokoban is a quite hard game, as actions are irreversible (you can get stuck) and the solution requires many actions (sparse rewards).
- MF methods are bad at this game as they learn through trials-and-(many)-errors.

Weber et al. (2017) Imagination-Augmented Agents for Deep Reinforcement Learning. arXiv:1707.06203.

Sokoban

I2A - Imagination-augmented agents

- The **model** learns to predict the next frame and the next reward based on the four last frames and the chosen action.

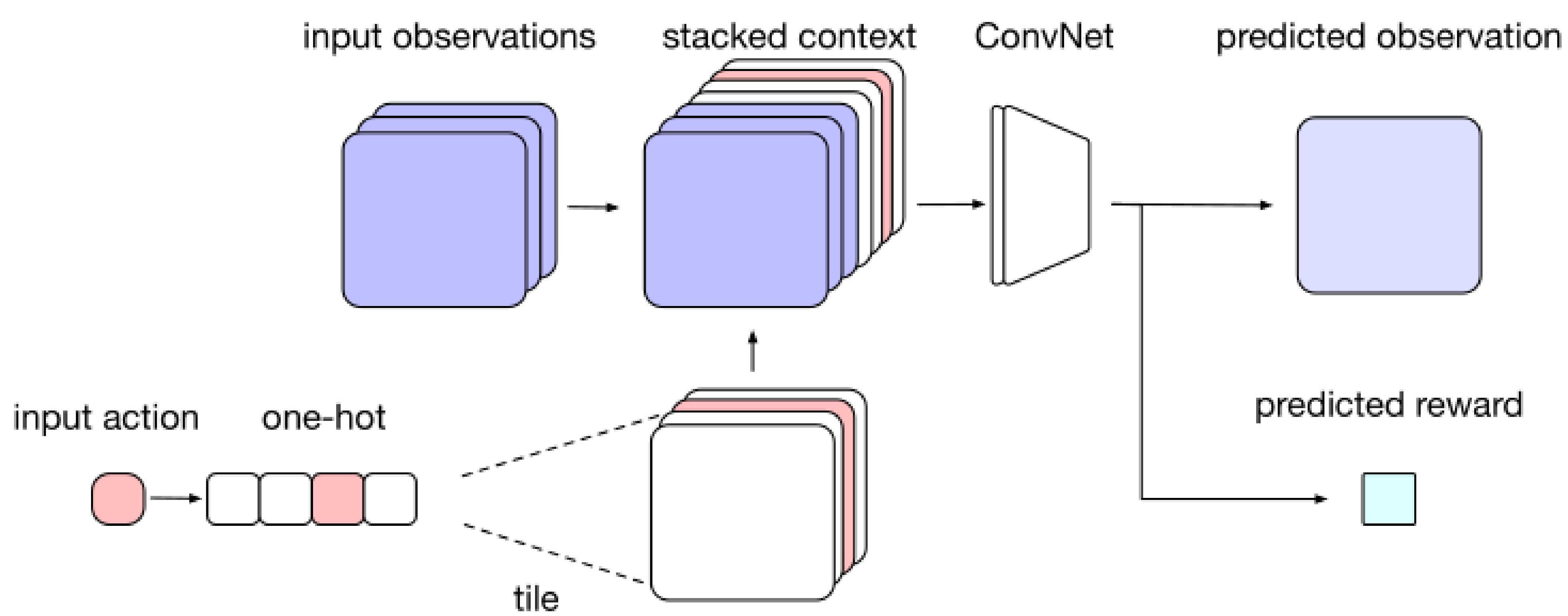
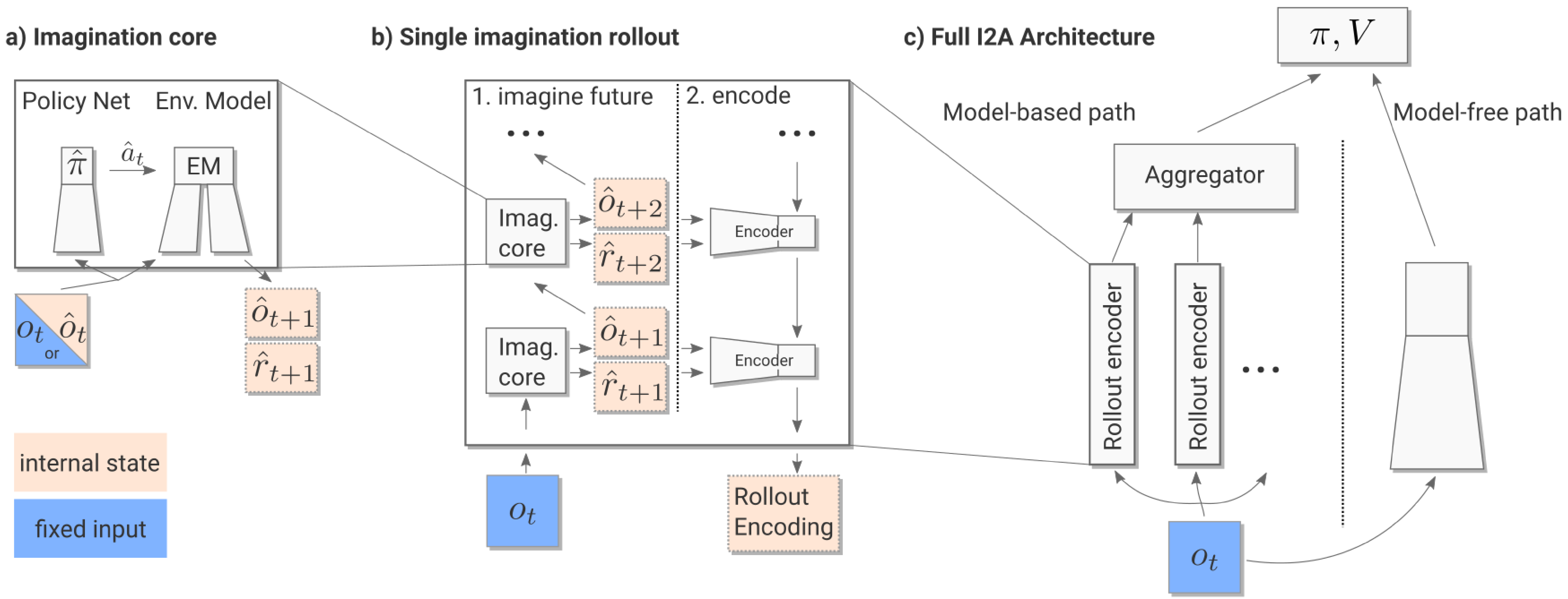


Figure 2: *Environment model.* The input action is broadcast and concatenated to the observation. A convolutional network transforms this into a pixel-wise probability distribution for the output image, and a distribution for the reward.

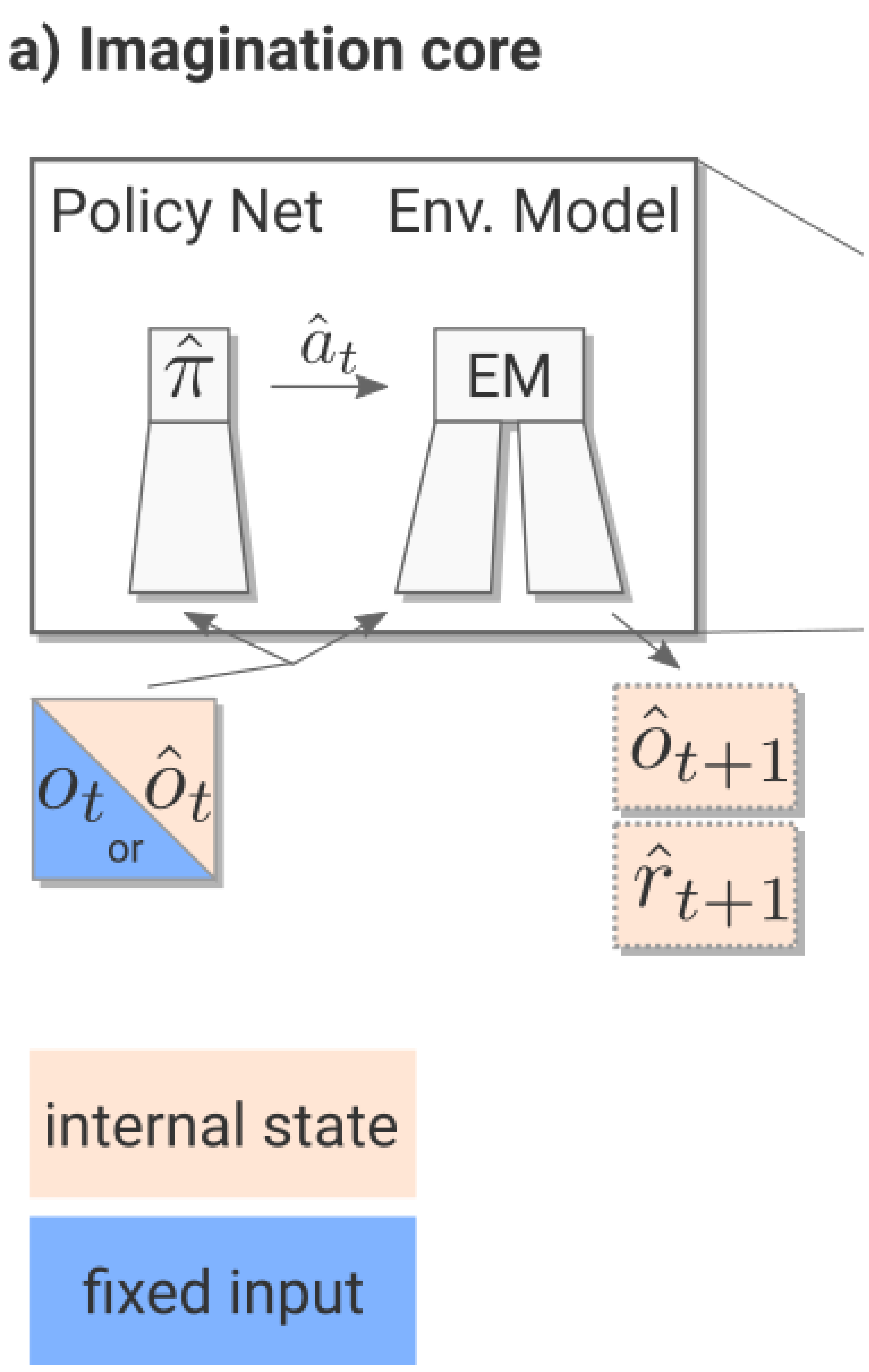
- It is a **convolutional autoencoder**, taking additionally an action a as input and predicting the next reward.
- It can be pretrained using a random policy, and later fine-tuned during training.

I2A - Imagination-augmented agents



Weber et al. (2017) Imagination-Augmented Agents for Deep Reinforcement Learning. arXiv:1707.06203.

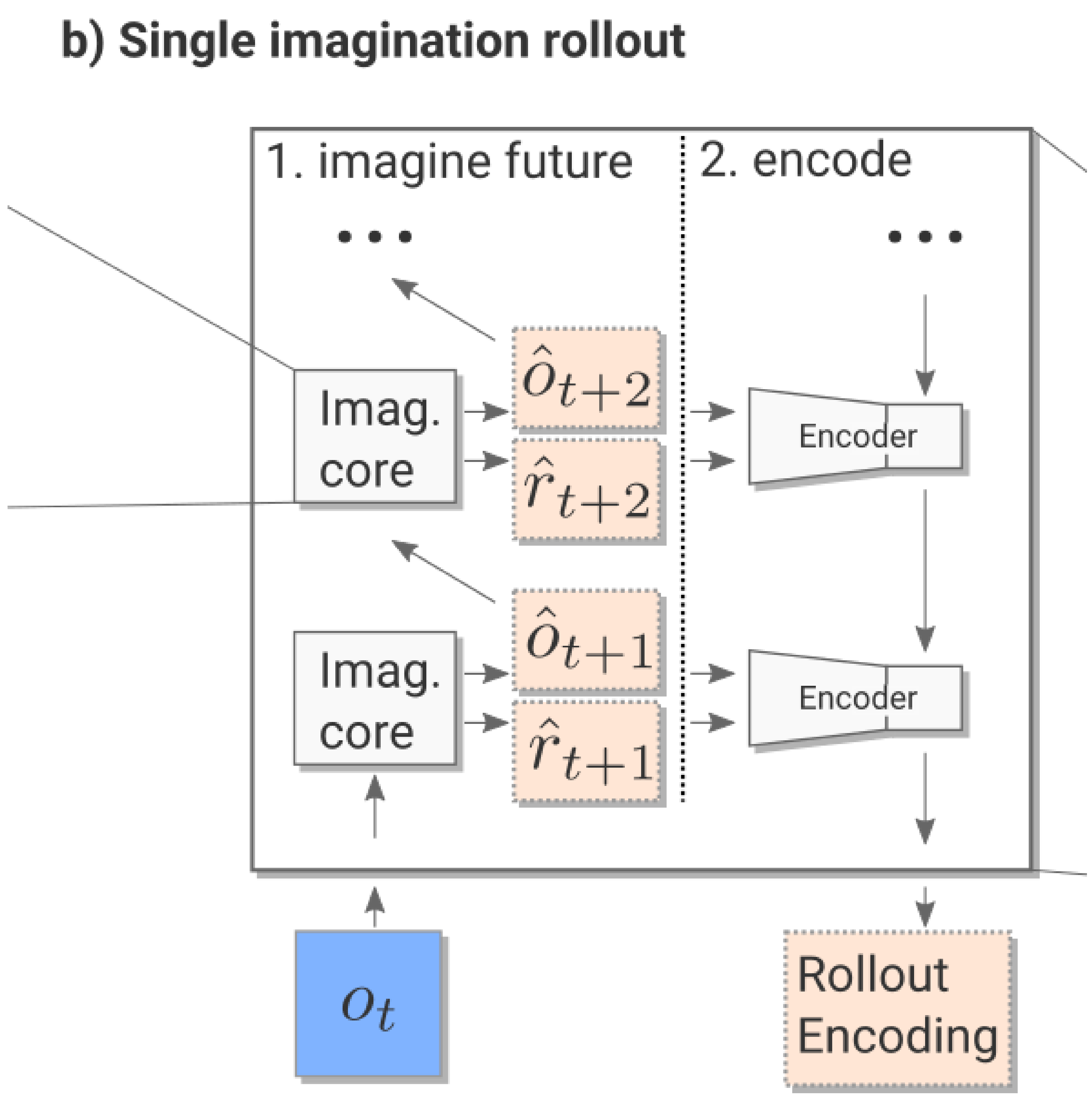
I2A - Imagination-augmented agents



- The **imagination core** is composed of the environment model $M(s, a)$ and a **rollout policy** $\hat{\pi}$.
- As Sokoban is a POMDP (partially observable), the notation uses **observation** o_t instead of states s_t, but it does not really matter here.
- The **rollout policy** $\hat{\pi}$ is a simple and fast policy. It does not have to be the trained policy π.
- It could even be a random policy, or a pretrained policy using for example A3C directly.
- In I2A, it is a **distilled policy** from the trained policy π (see later).
- Take home message: given the current observation o_t and a policy $\hat{\pi}$, we can predict the next observation $\hat{o}_{t+1}$ and the next reward $\hat{r}_{t+1}$.

Weber et al. (2017) Imagination-Augmented Agents for Deep Reinforcement Learning. arXiv:1707.06203.

I2A - Imagination-augmented agents



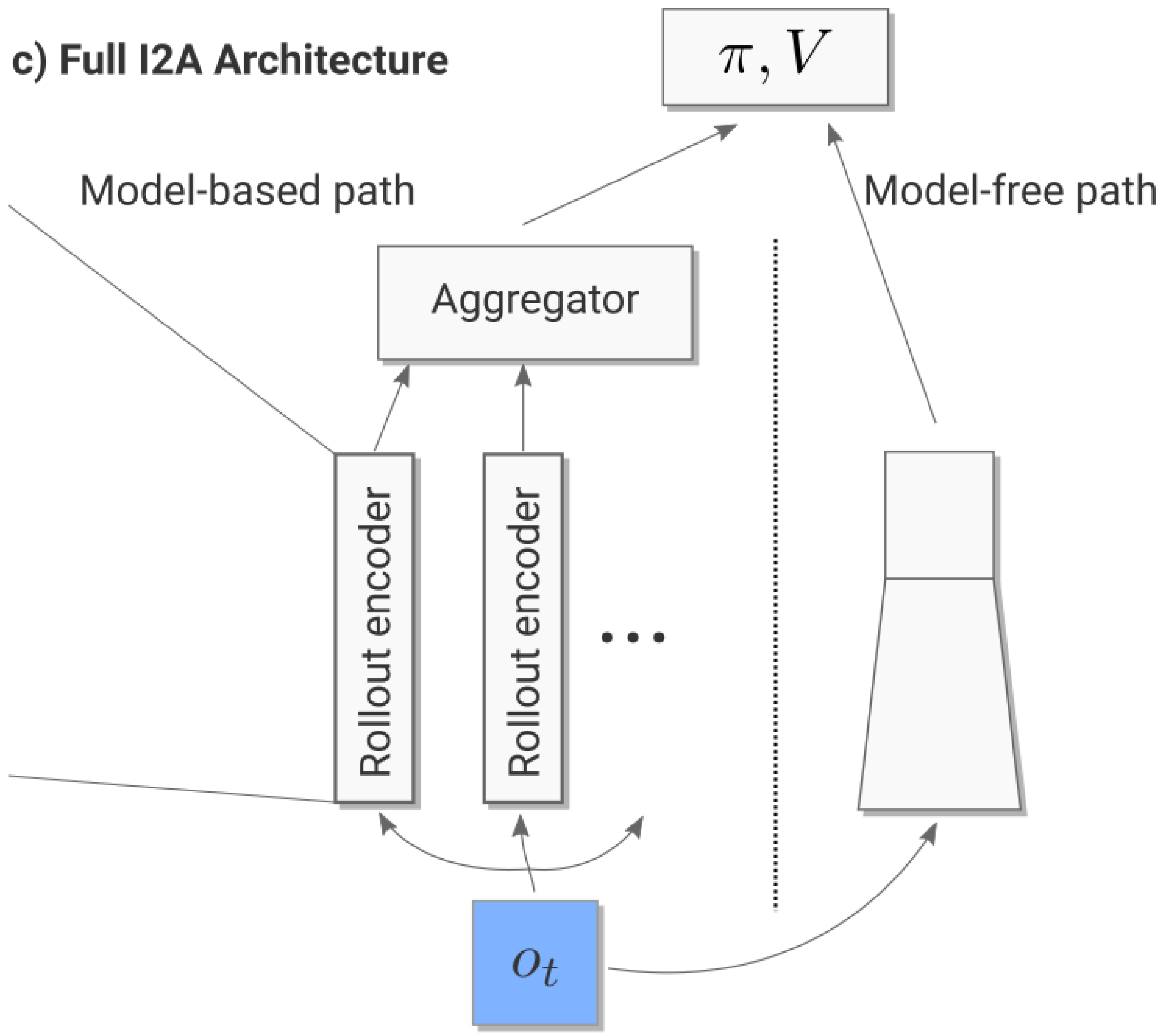
- The **imagination rollout module** uses the imagination core to predict iteratively the next τ frames and rewards using the current frame o_t and the rollout policy:

$$o_t \rightarrow \hat{o}_{t+1} \rightarrow \hat{o}_{t+2} \rightarrow \ldots \rightarrow \hat{o}_{t+\tau}$$

- The τ frames and rewards are passed **backwards** to a convolutional LSTM (from $t+\tau$ to t) which produces an embedding / encoding of the rollout.
- The output of the imagination rollout module is a vector e_i (the final state of the LSTM) representing the whole rollout, including the (virtually) obtained rewards.
- Note that because of the stochasticity of the rollout policy $\hat{\pi}$, different rollouts can lead to different encoding vectors.

Weber et al. (2017) Imagination-Augmented Agents for Deep Reinforcement Learning. arXiv:1707.06203.

I2A - Imagination-augmented agents



- For the current observation o_t, we then generate one **rollout** per possible action (5 in Sokoban):
  - What would happen if I do action 1?
  - What would happen if I do action 2?
  - etc.
- The resulting vectors are concatenated to the output of **model-free** path (a convolutional neural network taking the current observation as input).
- Altogether, we have a huge NN with weights θ (model, encoder, MF path) producing an input s_t to the **A3C** module.

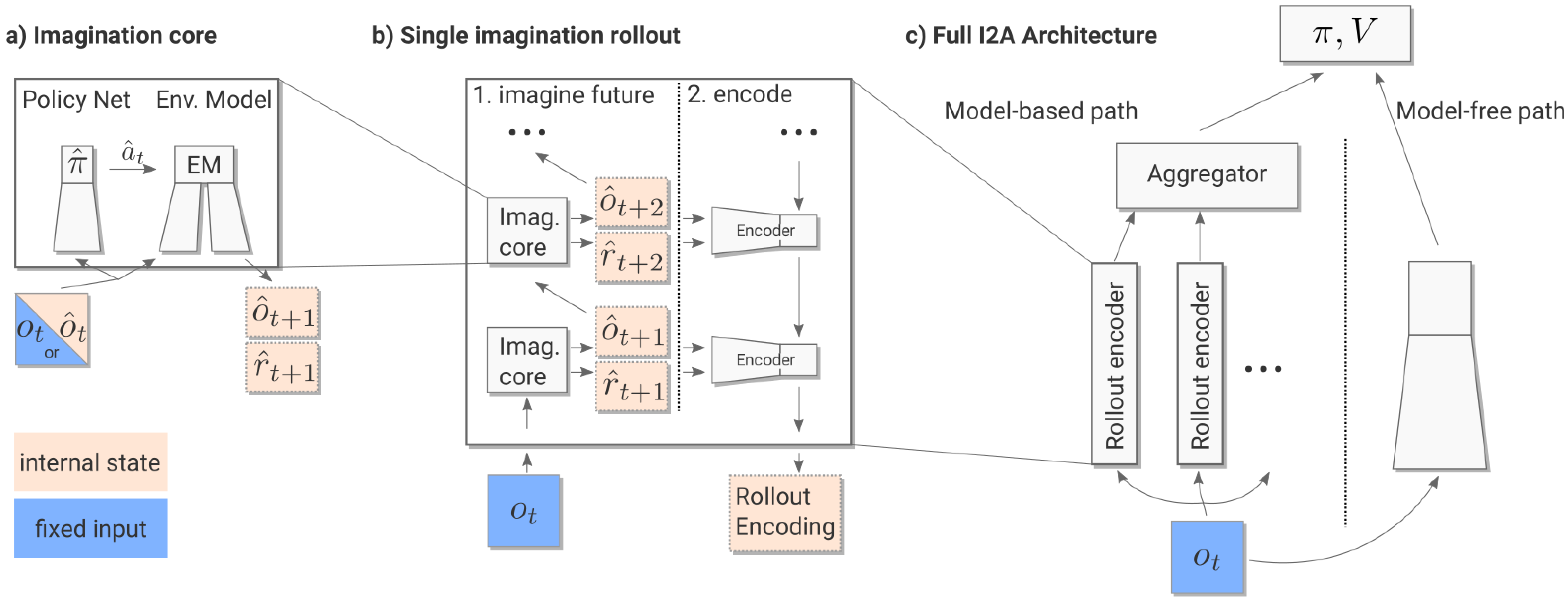
- We can then learn the policy π and value function V based on this input to maximize the returns:

$$\nabla_\theta \mathcal{J}(\theta) = \mathbb{E}_{s_t \sim \rho_\theta, a_t \sim \pi_\theta}[\nabla_\theta \log \pi_\theta(s_t, a_t) \, (\sum_{k=0}^{n-1} \gamma^k \, r_{t+k+1} + \gamma^n \, V_\varphi(s_{t+n}) - V_\varphi(s_t))]$$

$$\mathcal{L}(\varphi) = \mathbb{E}_{s_t \sim \rho_\theta, a_t \sim \pi_\theta}[(\sum_{k=0}^{n-1} \gamma^k \, r_{t+k+1} + \gamma^n \, V_\varphi(s_{t+n}) - V_\varphi(s_t))^2]$$

I2A - Imagination-augmented agents

- The complete architecture may seem complex, but everything is differentiable so we can apply backpropagation and train the network **end-to-end** using multiple workers.
- It is the A3C algorithm (MF), but **augmented** by MB rollouts, i.e. with explicit information about the future.

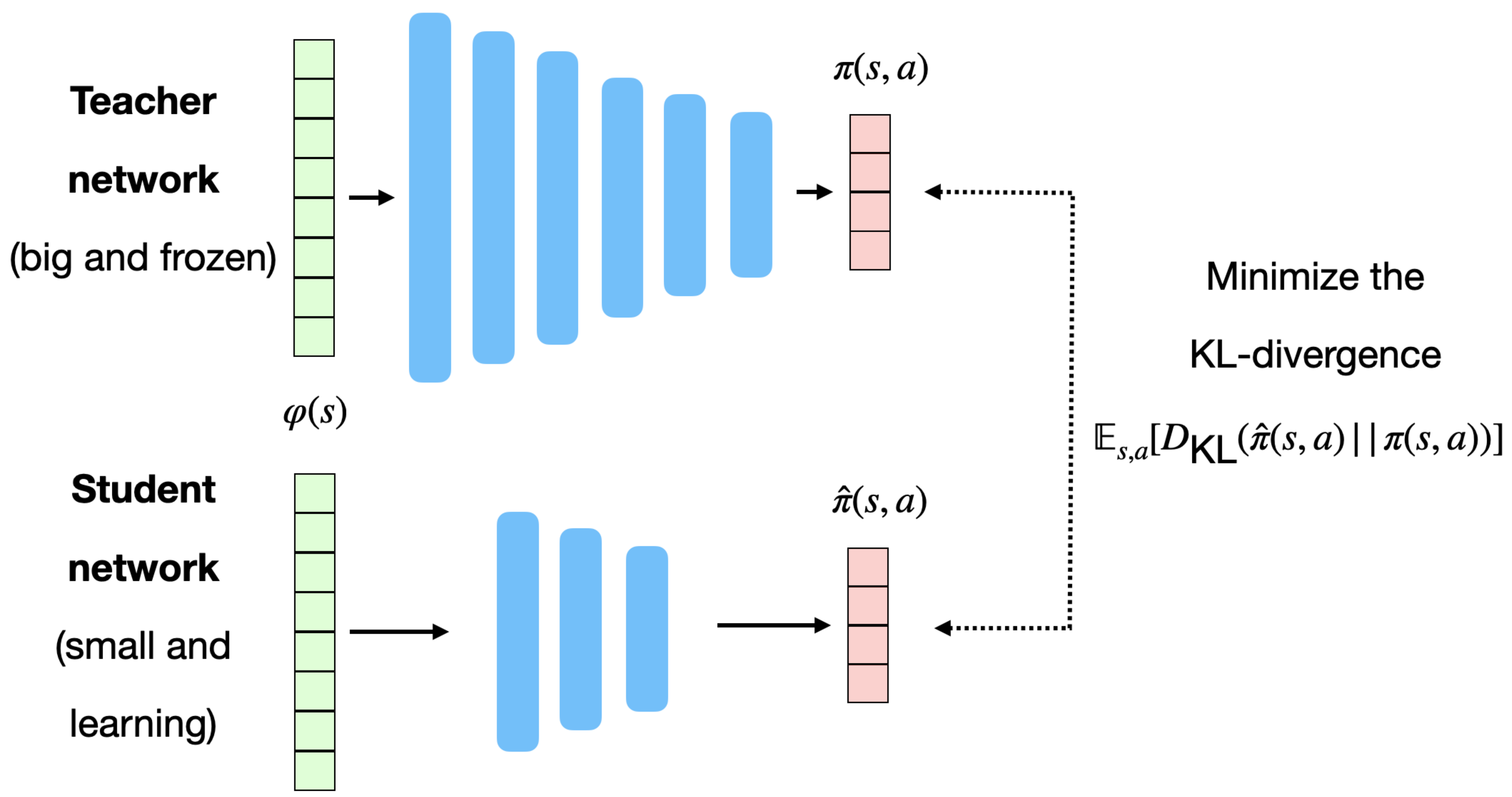


Policy distillation

- The **rollout policy** $\hat{\pi}$ is trained using **policy distillation** of the trained policy π.
- The small rollout policy network with weights $\hat{\theta}$ tries to copy the outputs $\pi(s, a)$ of the bigger policy network (A3C).
- This is a supervised learning task: just minimize the KL divergence between the two policies:

$$\mathcal{L}(\hat{\theta}) = \mathbb{E}_{s,a}[D_{\text{KL}}(\hat{\pi}(s, a)||\pi(s, a))]$$

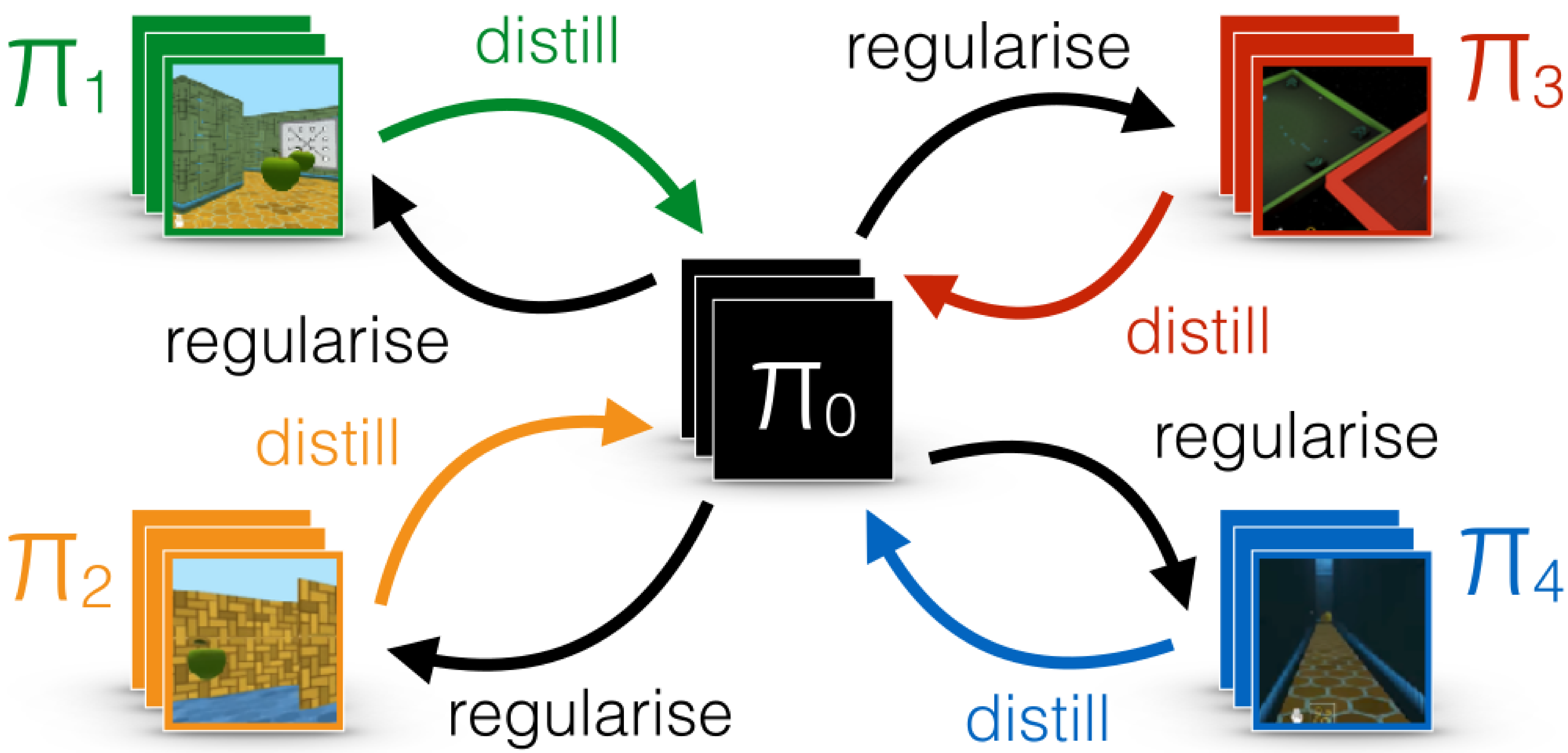
- As the network is smaller, it won't be as good as π, but its learning objective is easier.



Rusu et al. (2016) Policy Distillation. arXiv:1511.06295.

Distral : distill and transfer learning

- FYI: distillation can be used to ensure generalization over different environments.
- Each learning algorithms learns its own task, but tries not to diverge too much from a **shared policy**, which turns out to be good at all tasks.



Teh et al. (2017) Distral: Robust Multitask Reinforcement Learning. arXiv:1707.04175

I2A - Imagination-augmented agents

- Unsurprisingly, I2A performs better than A3C on Sokoban.
- The deeper the rollout, the better.

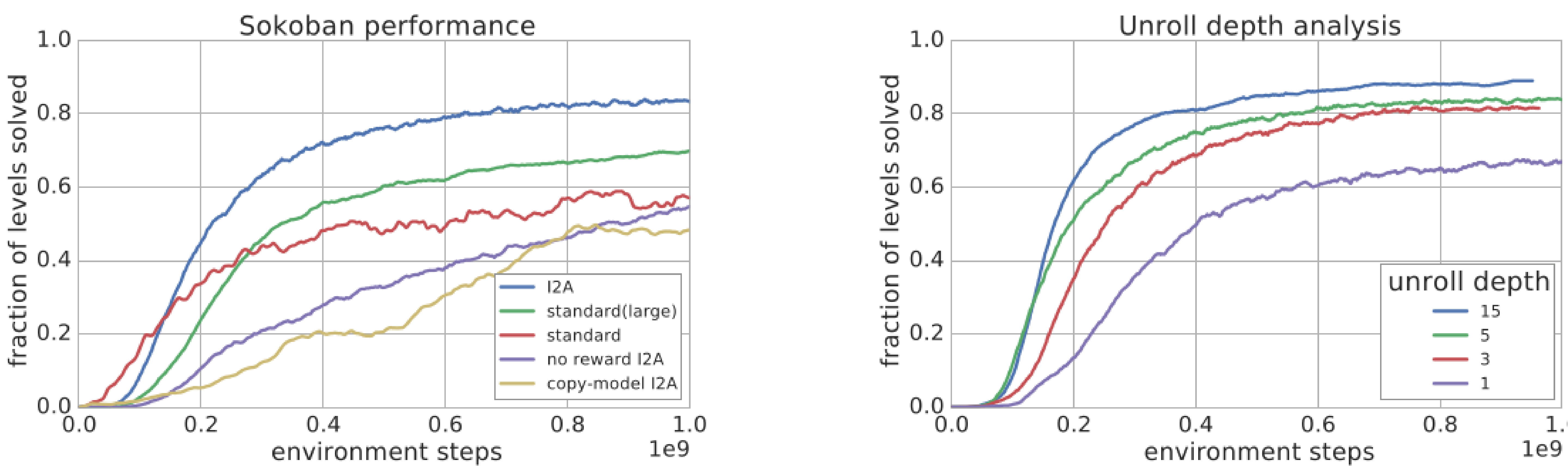


Figure 4: *Sokoban learning curves. Left:* training curves of I2A and baselines. Note that I2A use additional environment observations to pretrain the environment model, see main text for discussion. *Right:* I2A training curves for various values of imagination depth.

Teh et al. (2017) Distral: Robust Multitask Reinforcement Learning. arXiv:1707.04175

I2A - Imagination-augmented agents

- The model does not even have to be perfect: the MF path can compensate for imperfections.

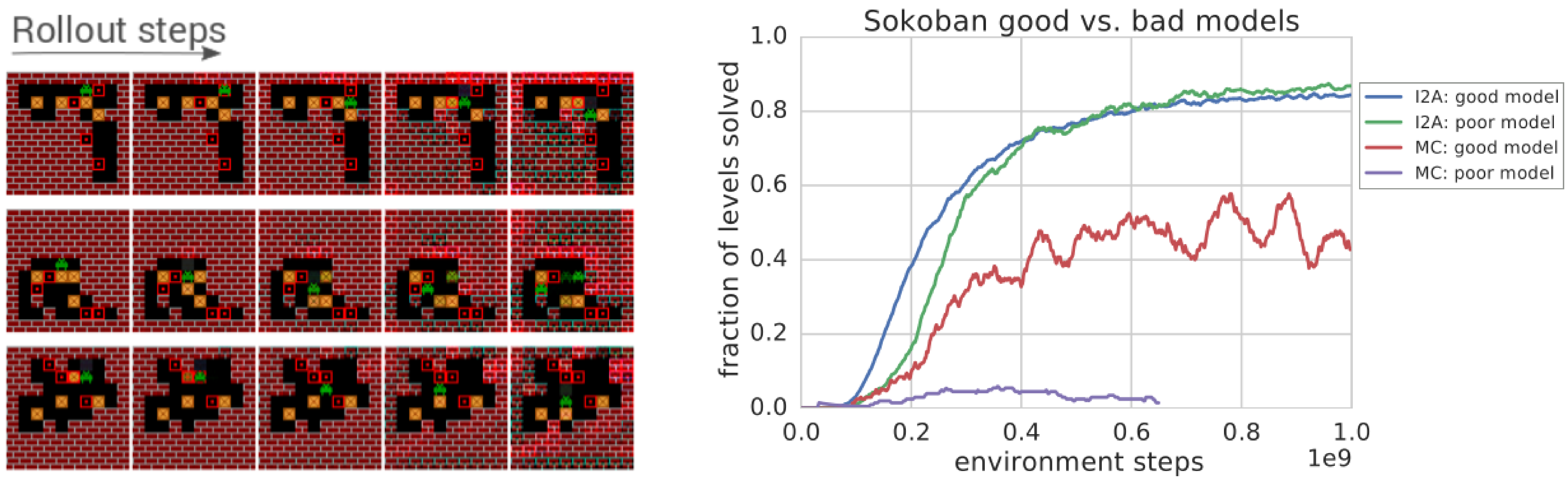
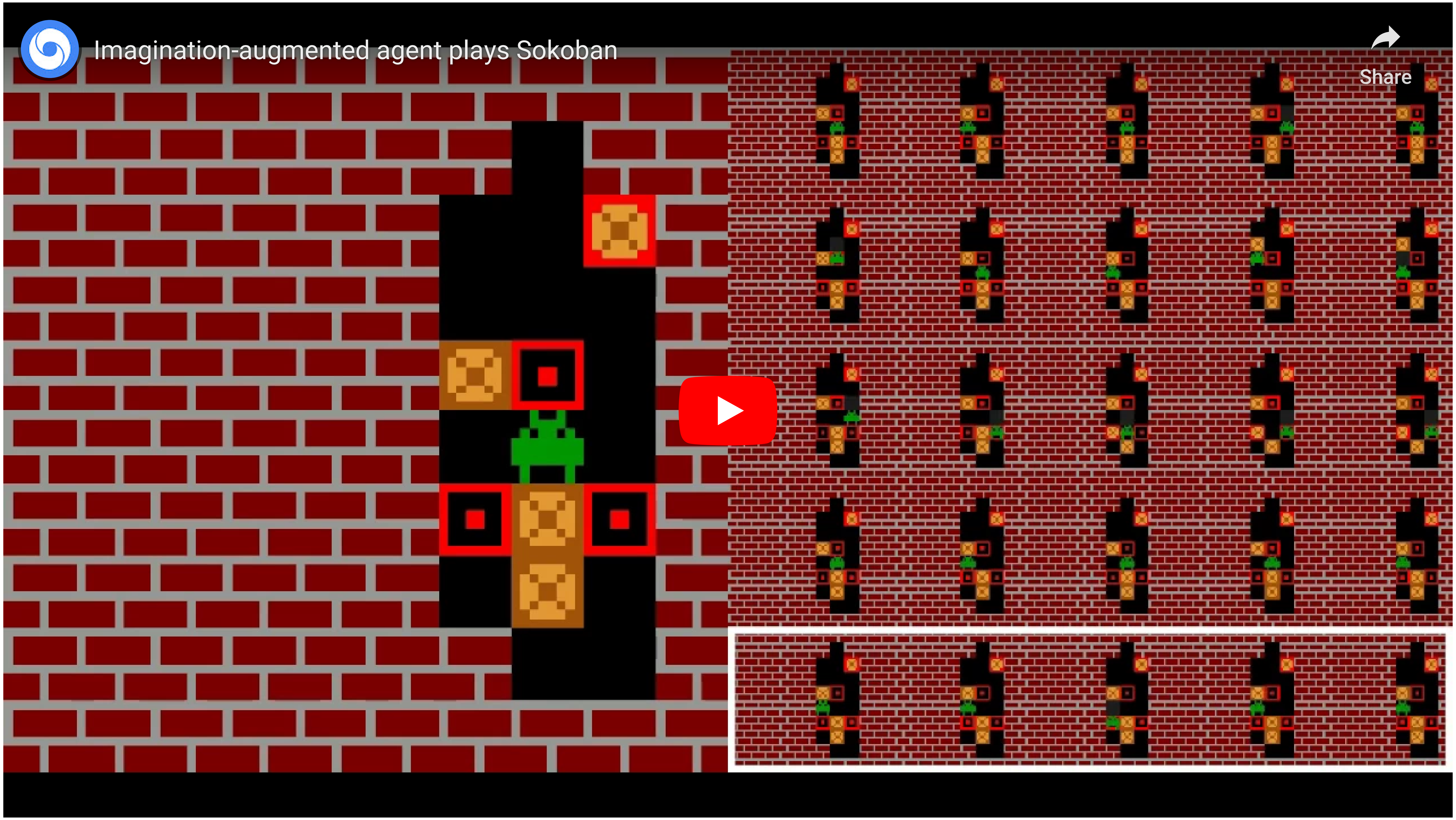


Figure 5: *Experiments with a noisy environment model. Left:* each row shows an example 5-step rollout after conditioning on an environment observation. Errors accumulate and lead to various artefacts, including missing or duplicate sprites. *Right:* comparison of Monte-Carlo (MC) search and I2A when using either the accurate or the noisy model for rollouts.

I2A - Sokoban



2 - Temporal difference models - TDM

TEMPORAL DIFFERENCE MODELS: MODEL-FREE DEEP RL FOR MODEL-BASED CONTROL

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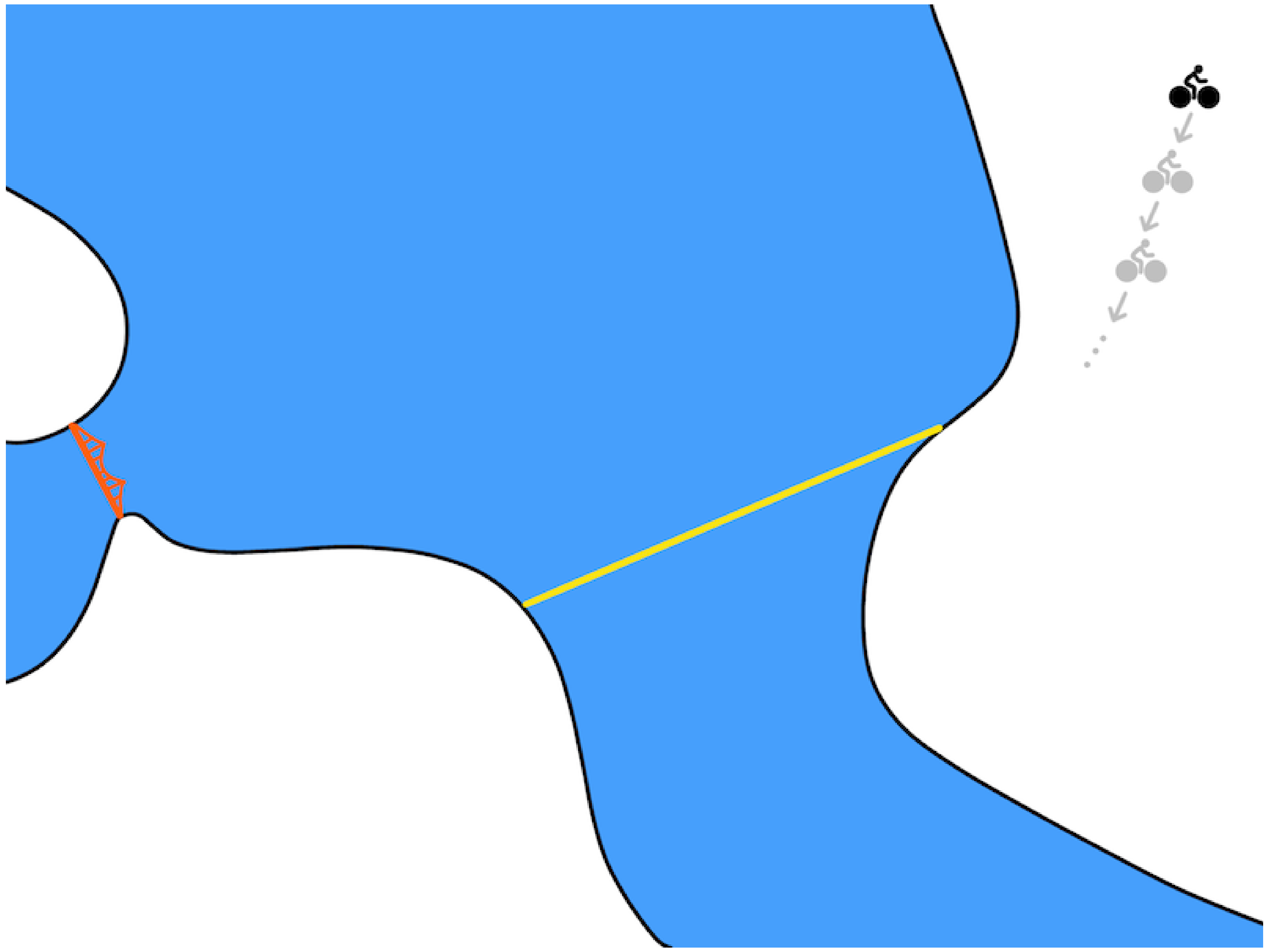
Pong et al. (2018) Temporal Difference Models: Model-Free Deep RL for Model-Based Control. arXiv:1802.09081

TDM

- One problem with model-based planning is the **discretization time step** (difference between t and $t+1$).
- It is determined by the action rate: how often a different action a_t has to be taken.
- In robotics, it could be below the millisecond, leading to very long trajectories in terms of steps.



Source: https://bairblog.github.io/2018/04/26/tdm/

- If you want to go from Berkeley to the Golden State bridge with your bike, planning over leg movements will be very expensive (long horizon).
- A solution is **multiple steps ahead planning**. Instead of learning a one-step model:

$$s_{t+1} = f_\theta(s_t, a_t)$$

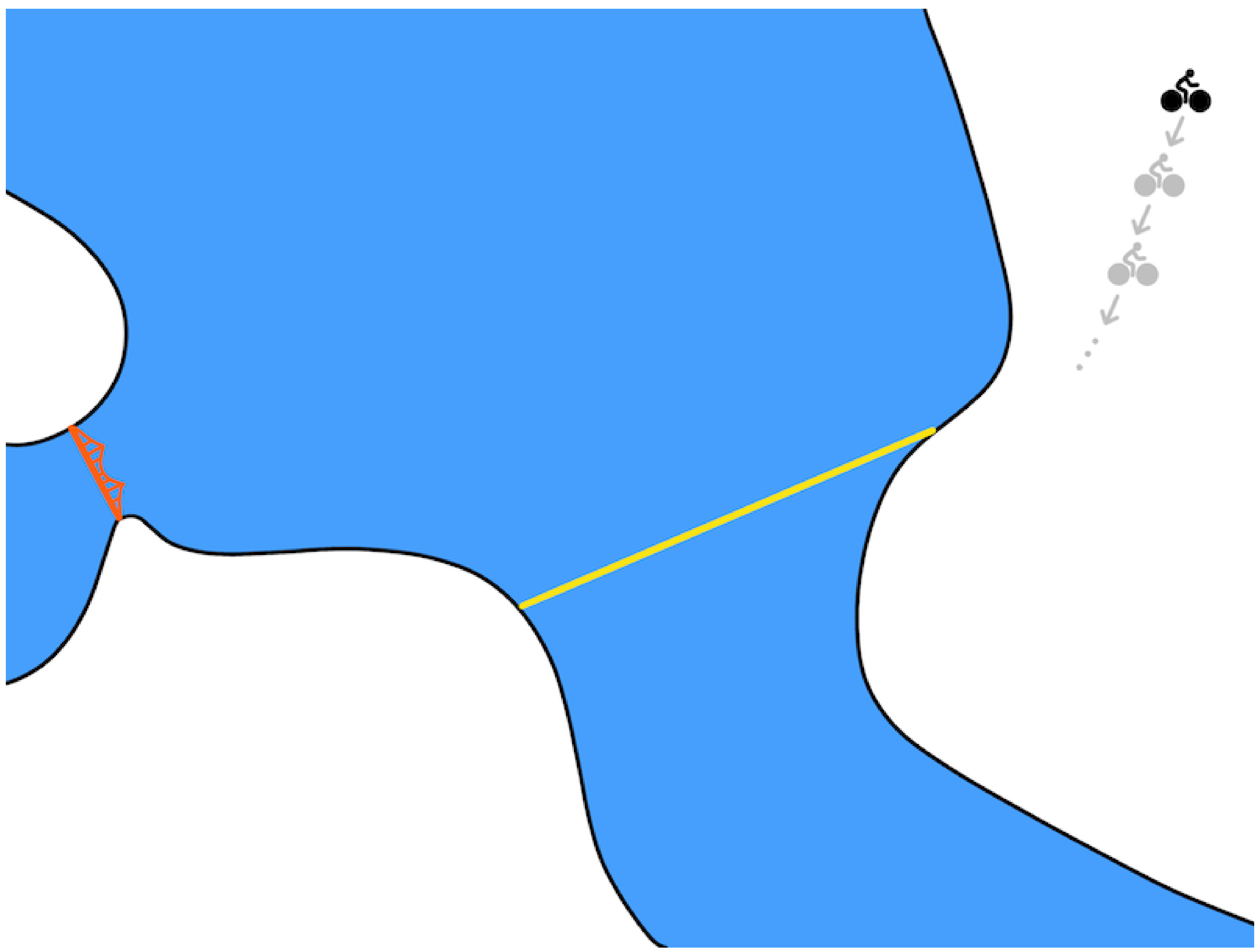
one learns to predict the state achieved in T steps using the current policy:

$$s_{t+T} = f_\theta(s_t, a_t, \pi)$$

- Planning and acting occur at different time scales.

TDM

- A problem with RL in general is how to define the **reward function**.



Source: https://bairblog.github.io/2018/04/26/tdm/

- If you goal is to travel from Berkeley to the Golden State bridge, which reward function should you use?
  - +1 at the bridge, 0 otherwise (sparse).
  - +100 at the bridge, -1 otherwise (sparse).
  - minus the distance to the bridge (dense).
- **Goal-conditioned RL** defines the reward function using the distance between the achieved state s_{t+1} and a **goal state** s_g:

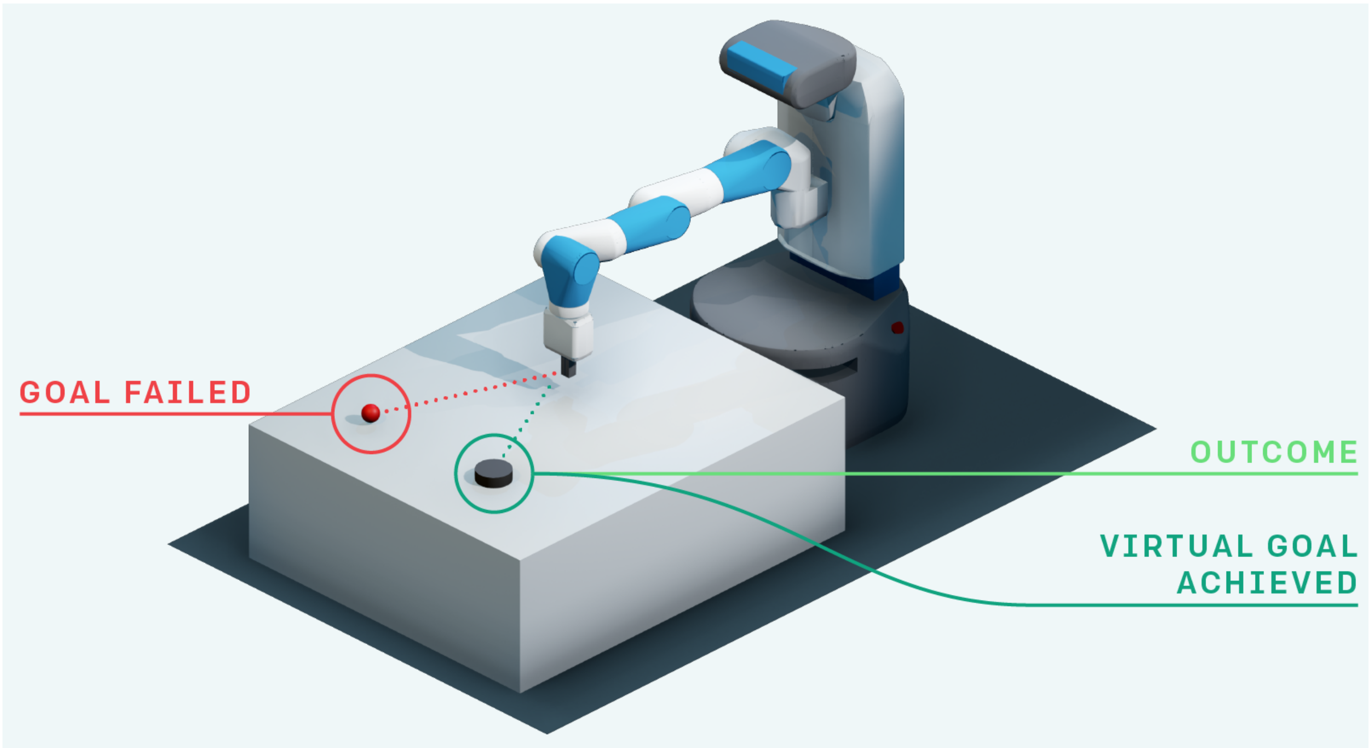
$$r(s_t, a_t, s_{t+1}) = -||s_{t+1} - s_g||$$

- An action is good if it brings the agent closer to its goal.
- The Euclidean distance works well for the biking example (e.g. using a GPS), but the metric can be adapted to the task.

Goal-conditioned RL

- One advantage is that you can learn multiple "tasks" at the same time with a single policy, not the only one hard-coded in the reward function.
- Another advantage is that it makes a better use of exploration by learning from mistakes: **hindsight experience replay** (HER, Andrychowicz et al., 2017).

- If your goal is to reach s_g but the agent generates a trajectory landing in $s_{g'}$, you can learn that this trajectory is good way to reach $s_{g'}$!
- In football, if you try to score a goal but end up doing a pass to a teammate, you can learn that this was a bad shot **and** a good pass.
- HER is a model-based method: you implicitly learn a model of the environment by knowing how to reach any position.

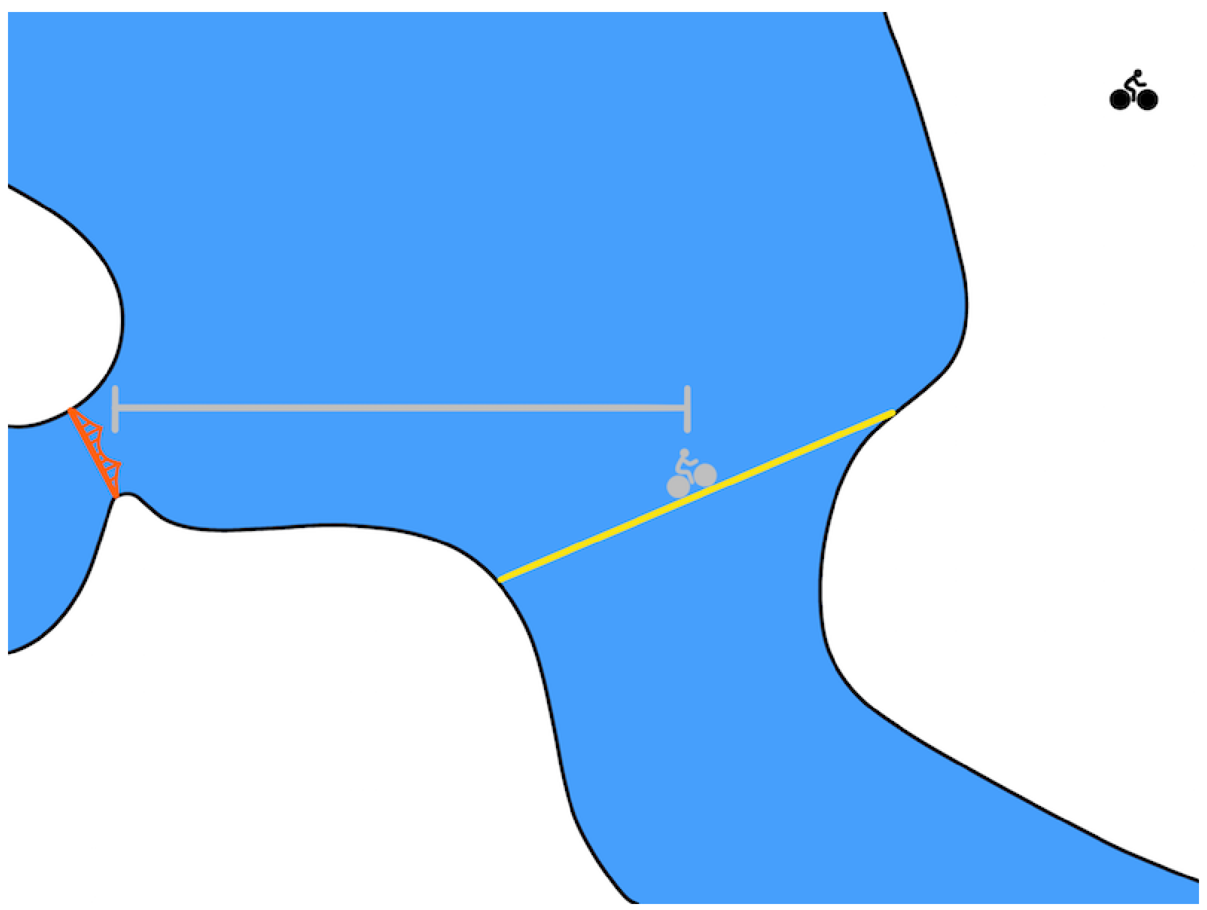


Source: https://openai.com/blog/ingredients-for-robotics-research/

- Exploration never fails: you always learn to do something, even if this was not your original goal.
- The principle of HER can be used in all model-free methods: DQN, DDPG, etc.

TDM

- Using the goal-conditioned reward function $r(s_t, a_t, s_{t+1}) = - || s_{t+1} - s_g ||$, how can we learn?



- TDM introduces goal-conditioned Q-value with a horizon T: $Q(s, a, s_g, T)$.
- The Q-value of an action should denote **how close** we will be from the goal s_g in T steps.
- If we can estimate these Q-values, we can use a planning algorithm such as MPC to find the action that will bring us closer to the goal easily:

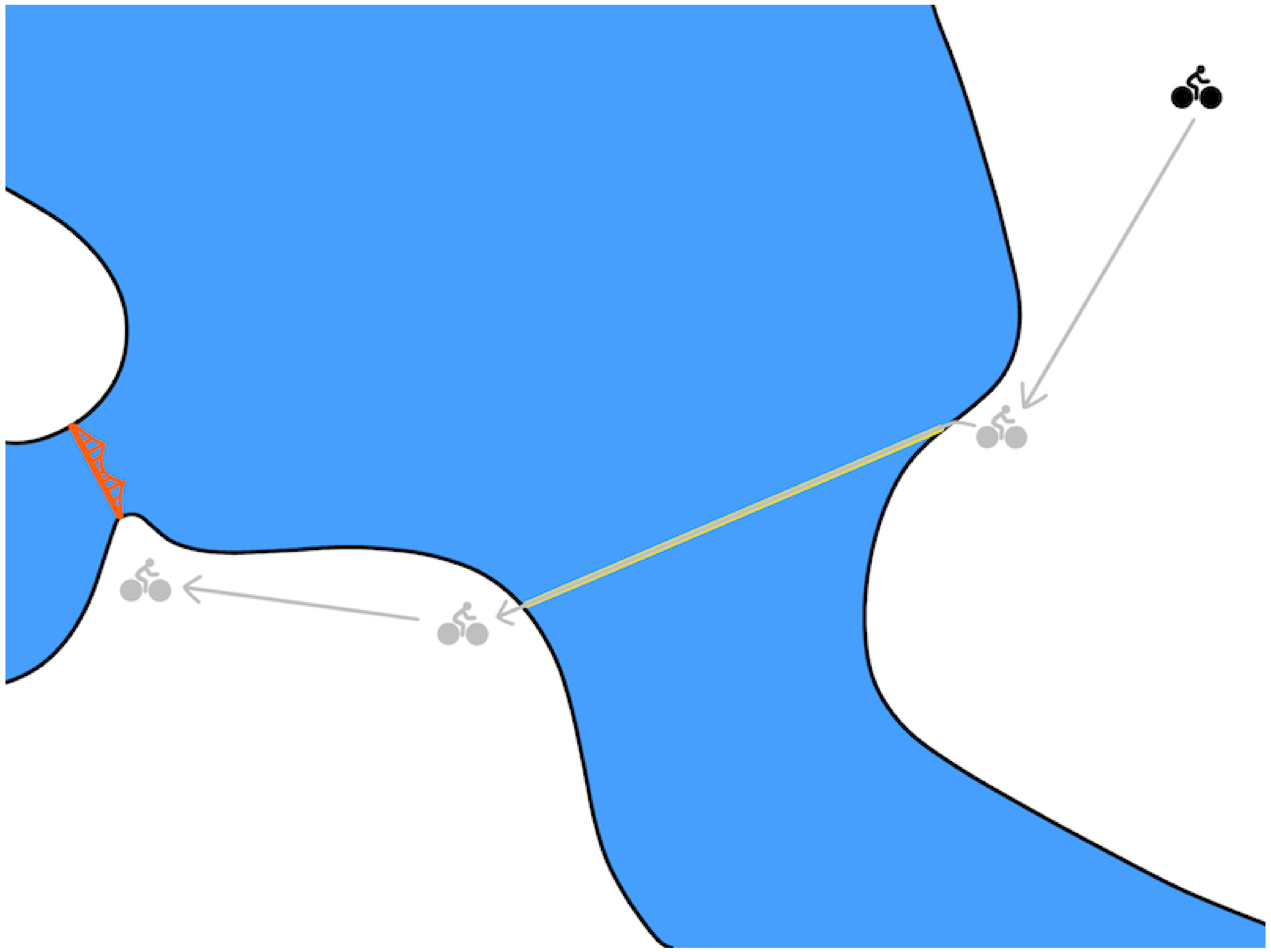
$$a^* = \arg \max_{a_t} \, r(s_{t+T}, a_{t+T}, s_{t+T+1})$$

- This corresponds to planning T steps ahead; which action should I do now in order to be close to the goal in T steps?

Source: https://bairblog.github.io/2018/04/26/tdm/

TDM

- If the horizon T is well chosen, we only need to plan over a small number of intermediary positions, not over each possible action.
- TDM is model-free on each subgoal, but model-based on the whole trajectory.



Source: https://bairblog.github.io/2018/04/26/tdm/

TDM

- How can we learn the goal-conditioned Q-values $Q(s, a, s_g, T)$ with a **model**?
- TDM introduces a recursive relationship for the Q-values:

$$Q(s, a, s_g, T) = \begin{cases} \mathbb{E}_{s'} [r(s, a, s')] \text{ if } T = 0 \\ \\ \mathbb{E}_{s'} [\max_a \; Q(s', a, s_g, T-1)] \text{ otherwise.} \end{cases}$$

$$= \mathbb{E}_{s'} [r(s, a, s') \, \mathbb{1}(T = 0) + \max_a \; Q(s', a, s_g, T-1) \, \mathbb{1}(T \neq 0)]$$

- If we plan over $T = 0$ steps, i.e. immediately after the action (s, a), the Q-value is the remaining distance to the goal from the next state s'.
- Otherwise, it is the Q-value of the greedy action in the next state s' with an horizon $T-1$ (one step shorter).
- This allows to learn the Q-values from **single transitions** (s_t, a_t, s_{t+1}):
  - with $T = 0$, the target is the remaining distance to the goal.
  - with $T > 0$, the target is the Q-value of the next action at a shorter horizon.

TDM

- The critic learns to minimize the prediction error **off-policy**:

$$
\begin{aligned}
\mathcal{L}(\theta) = & \mathbb{E}_{s_t, a_t, s_{t+1} \in \mathcal{D}} [\\
& (r(s_t, a_t, s_{t+1}) \, 1(T = 0) + \max_a \, Q(s_{t+1}, a, s_g, T-1) \, 1(T \neq 0) - Q(s_t, a_t, s_g, T))^2 \\
&]
\end{aligned}
$$

- This is a model-free Q-learning-like update rule, that can be learned by any off-policy value-based algorithm (DQN, DDPG) and an experience replay memory.
- The cool trick is that, with a single transition (s_t, a_t, s_{t+1}), you can train the critic with:
  - different horizons T, e.g. between 0 and $T_{\max}$.
  - different goals s_g. You can sample any achievable state as a goal, including the "true" s_{t+T} (hindsight).
- You do not only learn to reach s_g, but any state! TDM learns a lot of information from a single transition, so it has a very good sample complexity.

Summary of TDM

- TDM learns to break long trajectories into finite horizons (model-based planning) by learning model-free (Q-learning updates).
- The critic learns how good an action (s, a) is order to reach a state s_g in T steps.

$$Q(s, a, s_g, T) = \mathbb{E}_{s'} [r(s, a, s') \, 1(T=0) + \max_a \, Q(s', a, s_g, T-1) \, 1(T \neq 0)]$$

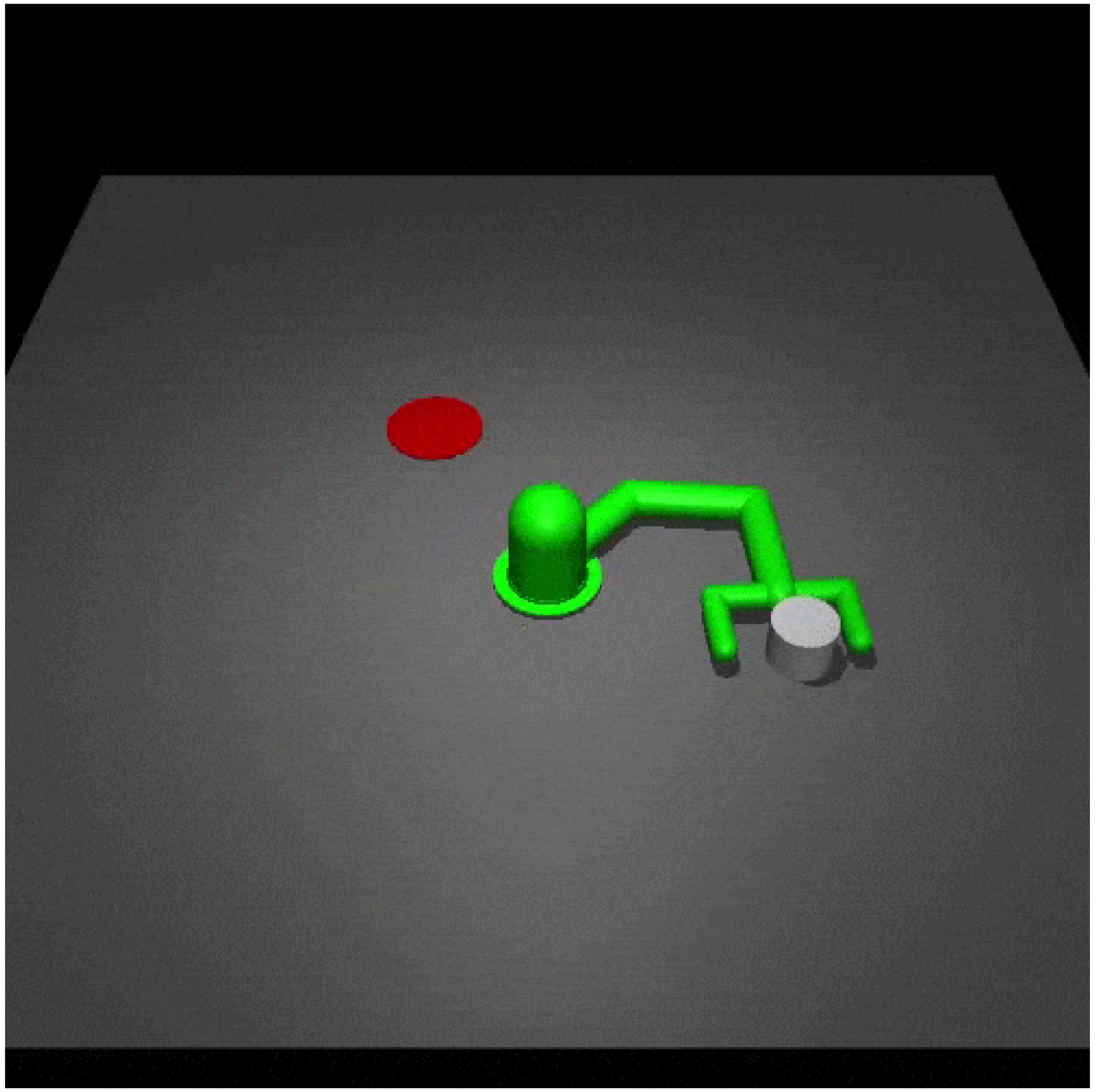
- The actor uses MPC planning to iteratively select actions that bring us closer to the goal in T steps:

$$a_t = \arg \max_a \, Q(s_t, a, s_g, T)$$

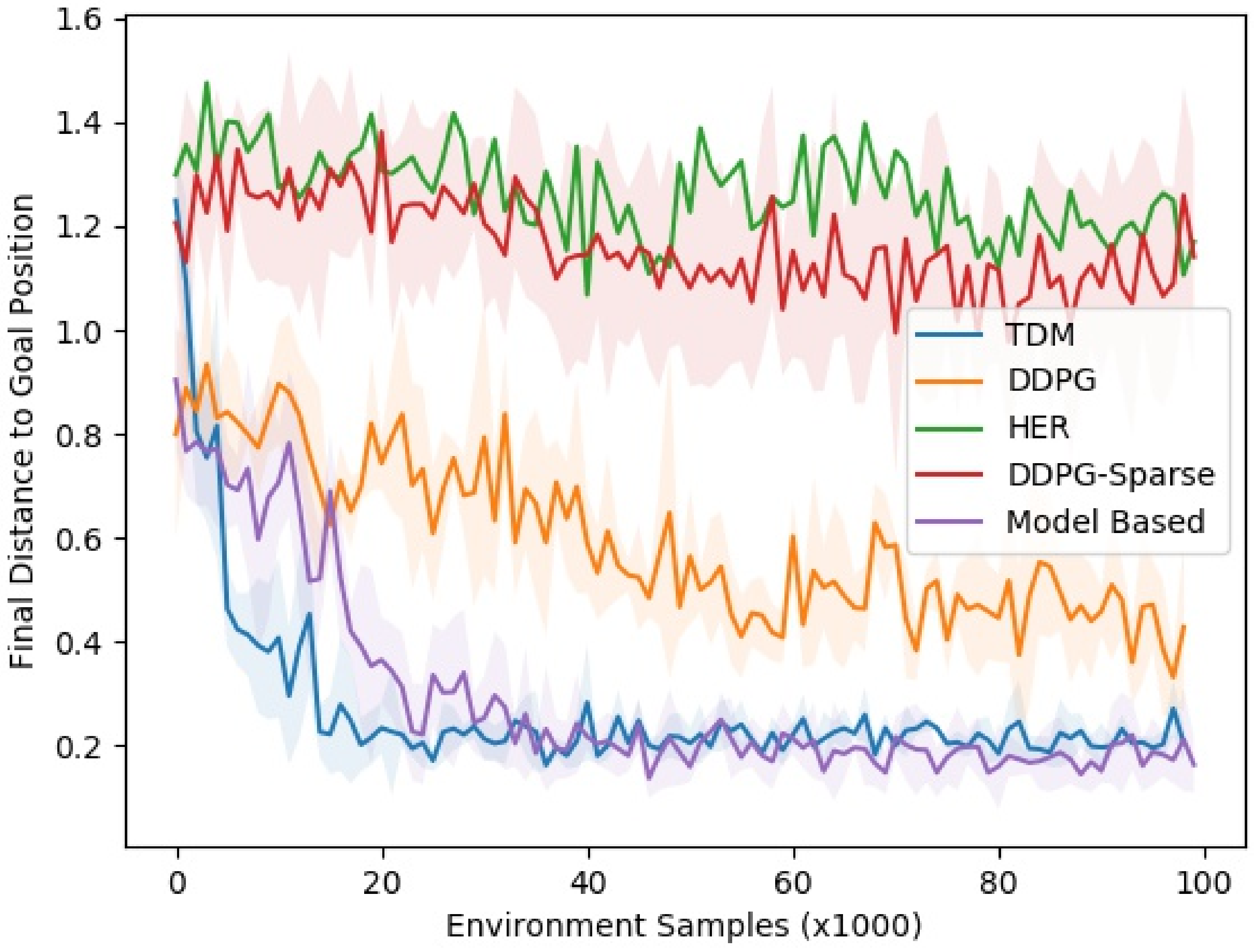
- The argmax can be estimated via sampling.
- TDM is a model-based method in disguise: it does predict the next state directly, but how much closer it will be to the goal via Q-learning.

TDM results

- For problems where the model is easy to learn, the performance of TDM is on par with model-based methods (MPC).



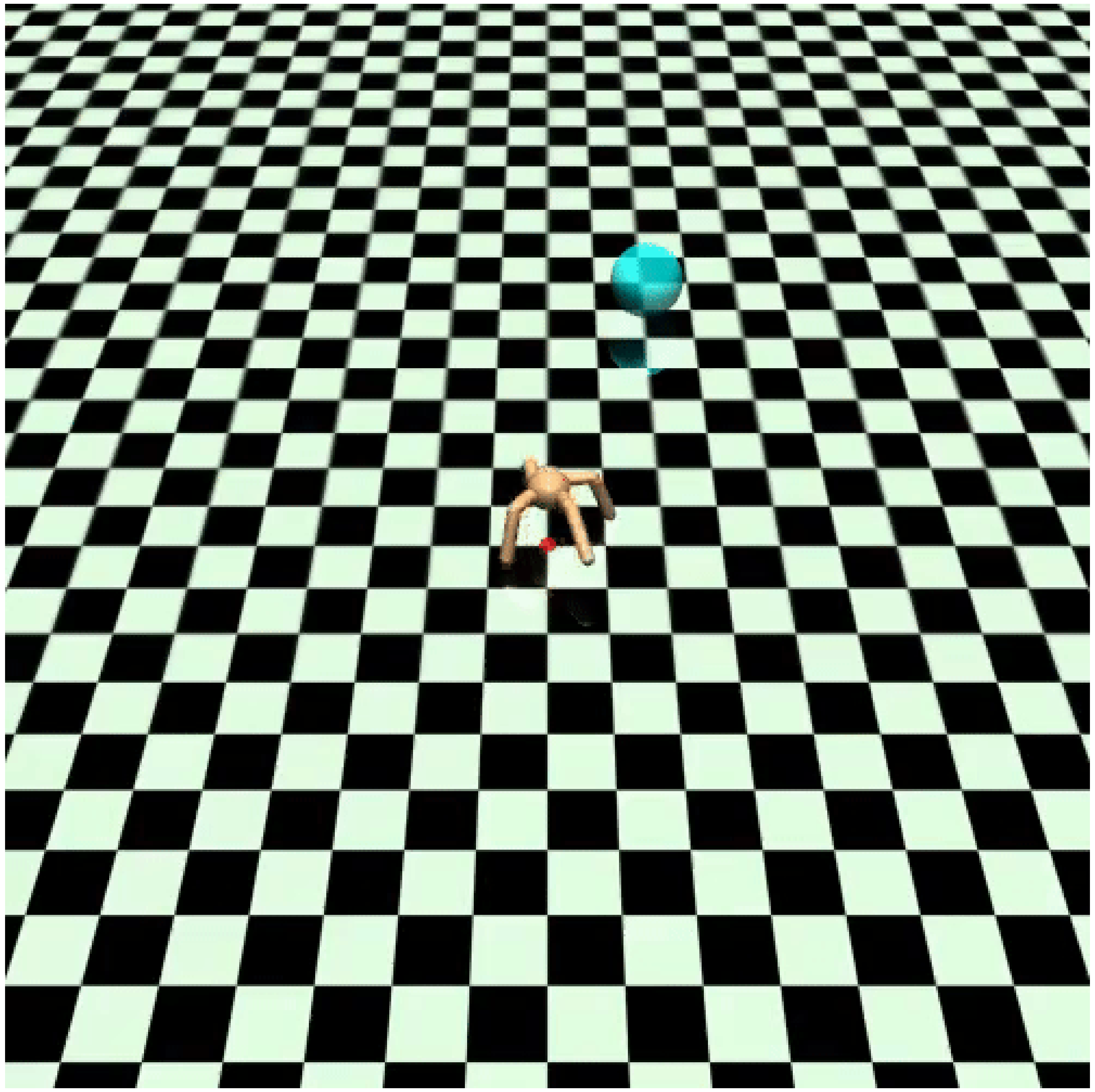
- Model-free methods have a much higher sample complexity.
- TDM learns much more from single transitions.



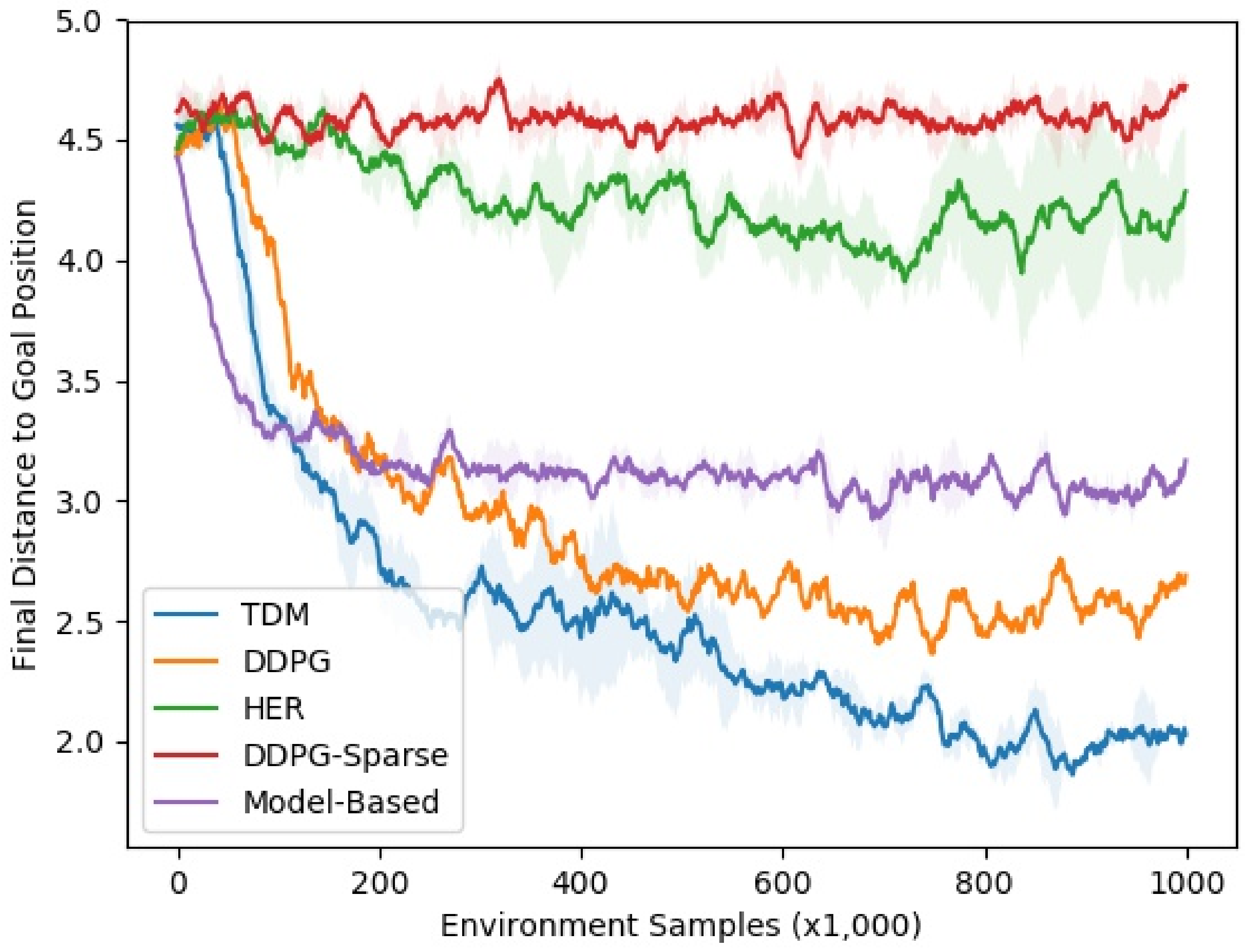
Source: https://bairblog.github.io/2018/04/26/tdm/

TDM results

- For problems where the model is complex to learn, the performance of TDM is on par with model-free methods (DDPG).



- Model-based methods suffer from model imprecision on long horizons.
- TDM plans over shorter horizons T.



Source: https://bairblog.github.io/2018/04/26/tdm/

3 - World models

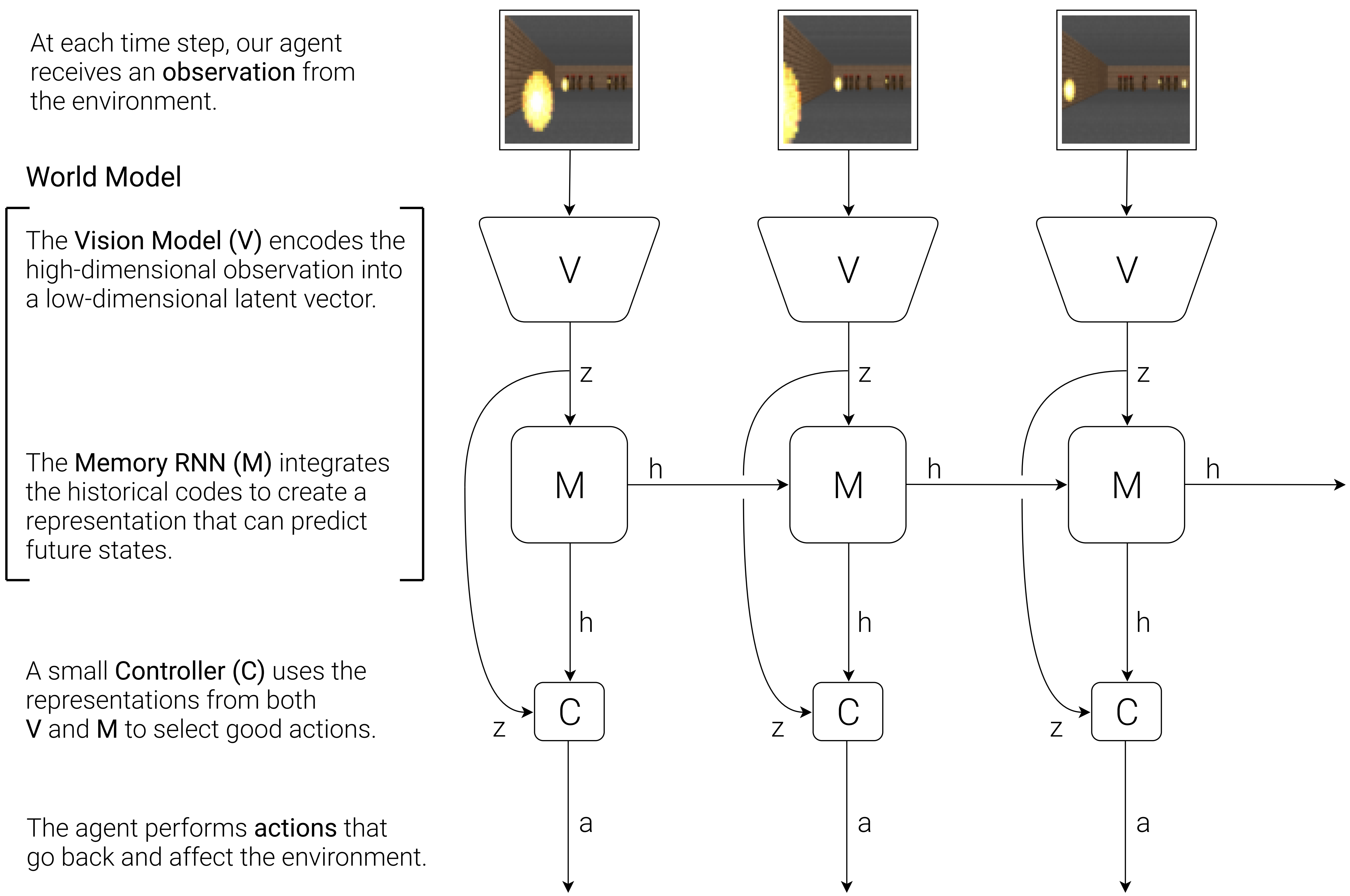
World Models

David Ha [1] **Jürgen Schmidhuber** [2 3]

https://worldmodels.github.io/

World models

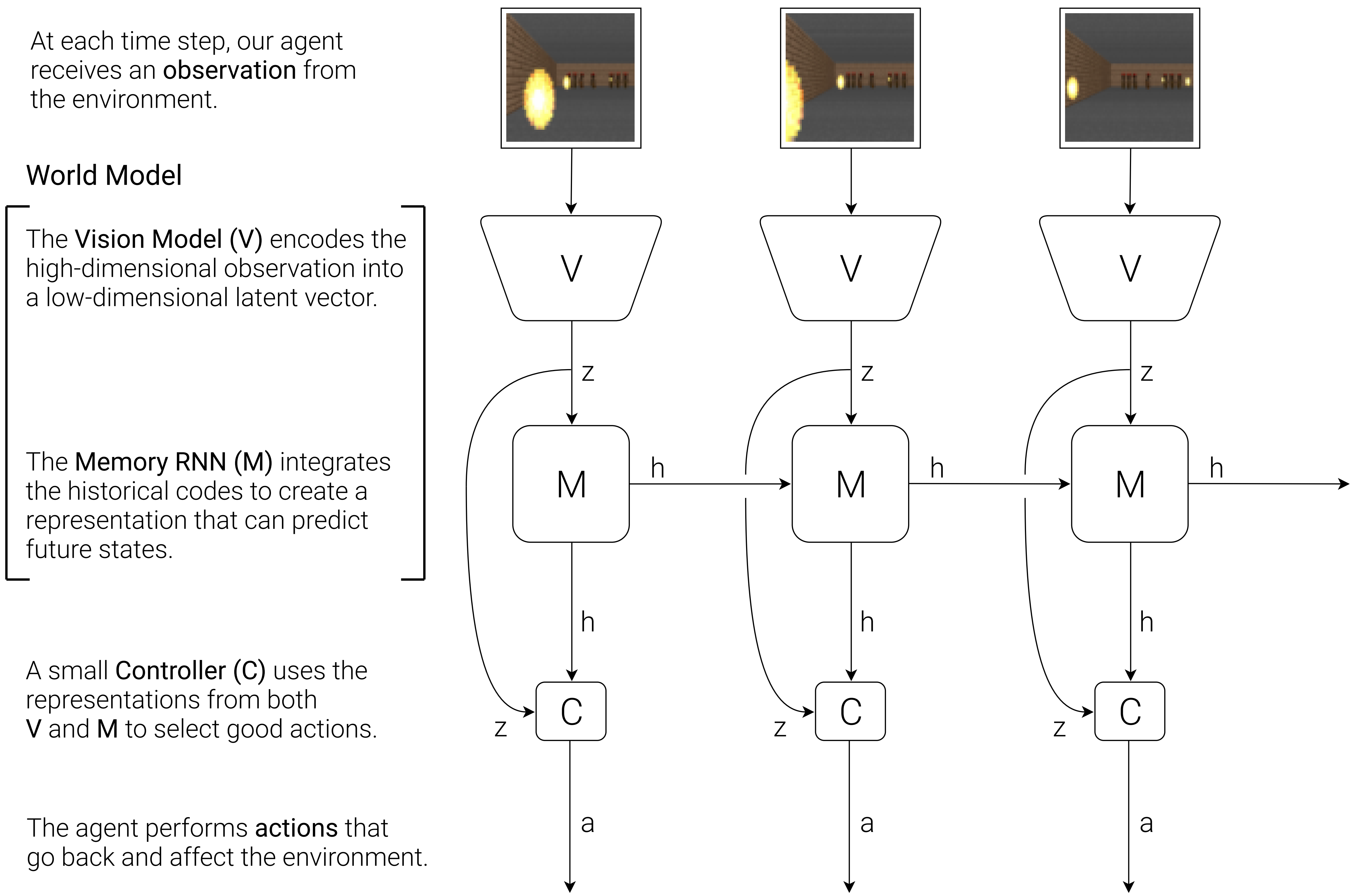
- The core idea of **world models** is to explicitly separate the **world model** (what will happen next) from the **controller** (how to act).
- Deep RL NN are usually small, as rewards do not contain enough information to train huge networks.



https://worldmodels.github.io/

World models

- A huge **world model** can be efficiently trained by supervised or unsupervised methods.
- A small **controller** should not need too many trials if its input representations are good.



https://worldmodels.github.io/

The Vizdoom Take Cover environment

The media could not be loaded, either because the server or network failed or because the format is not supported.

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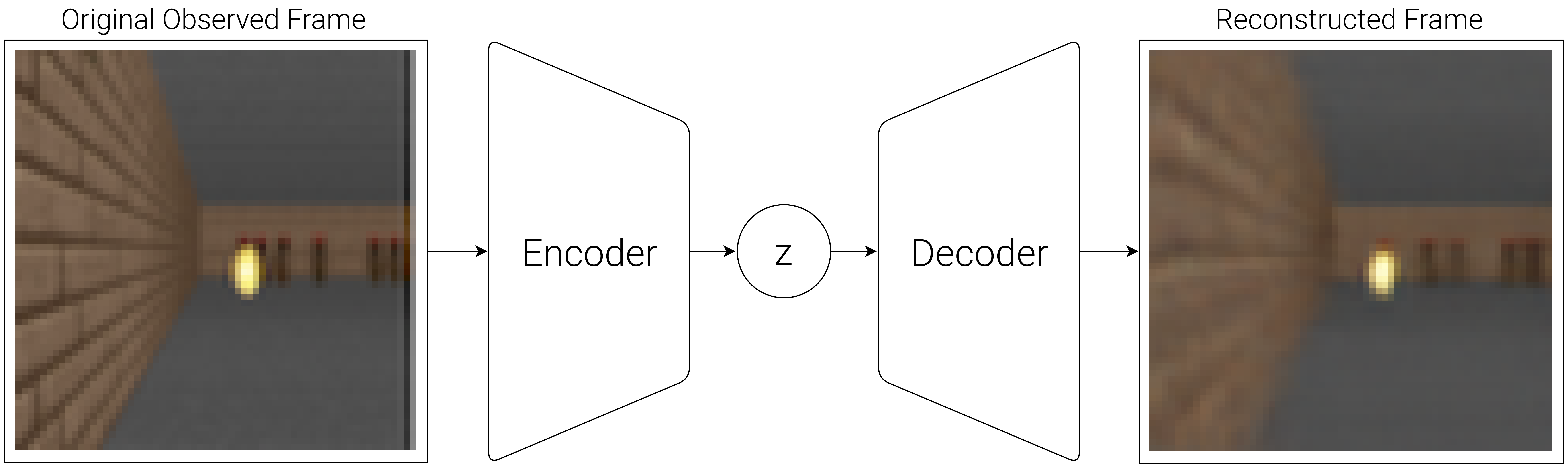
http://vizdoom.cs.put.edu.pl/, https://worldmodels.github.io/

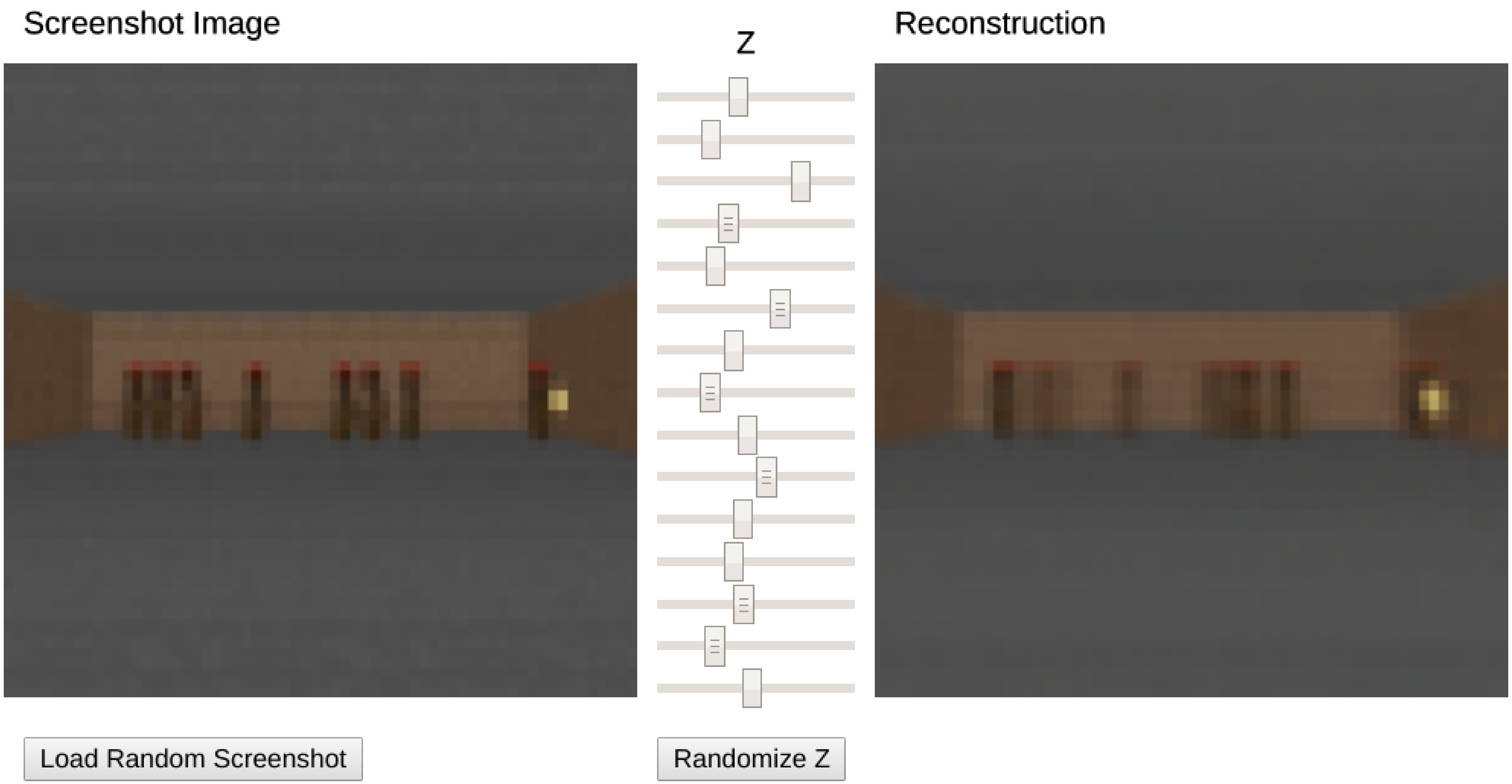
World models

- The vision module V is trained as a **variational autoencoder** (VAE) on single frames of the game.
- The latent vector $\mathbf{z}_t$ contains a compressed representation of the frame $\mathbf{o}_t$.



https://worldmodels.github.io/

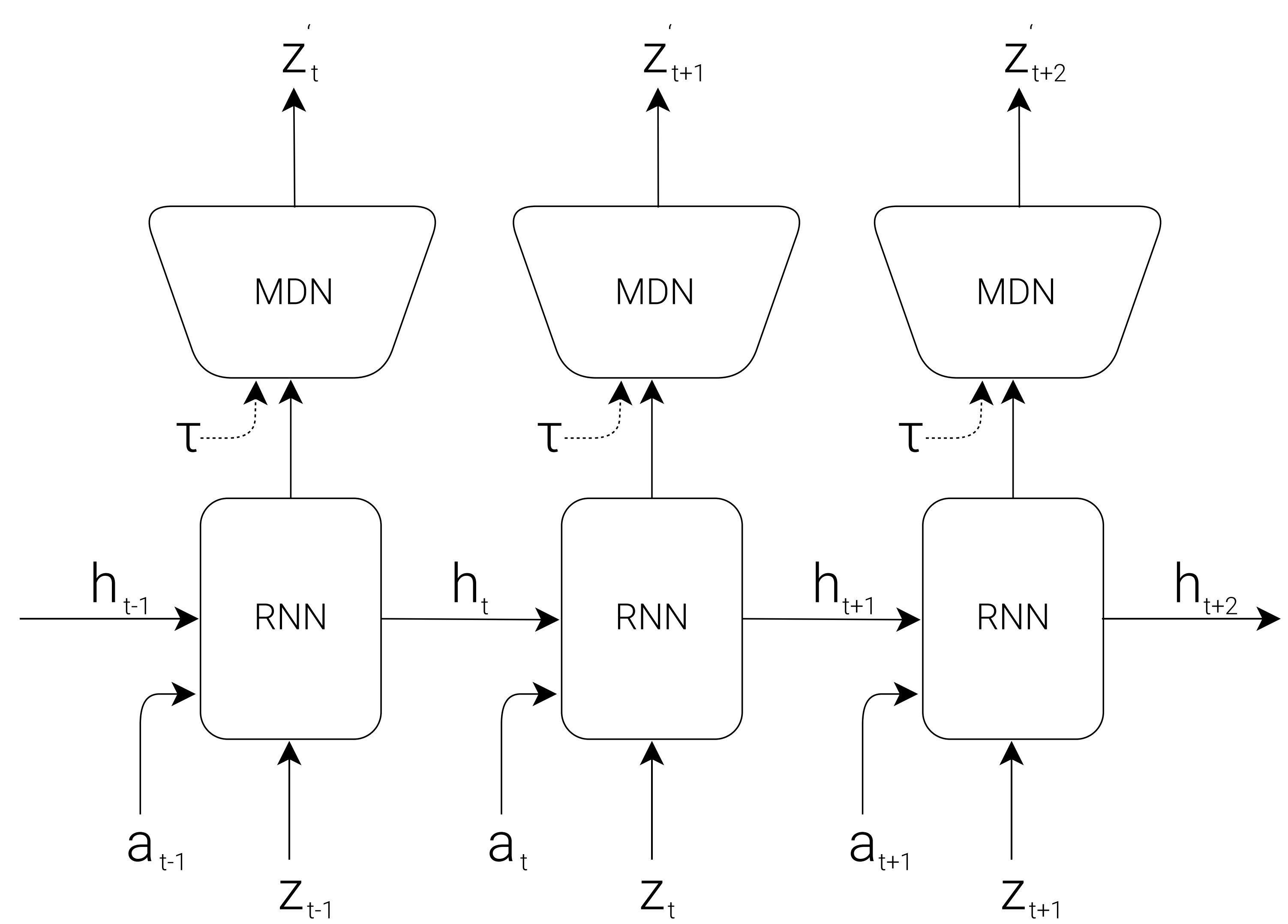
World models



- Go to https://worldmodels.github.io/ for an interactive demo.

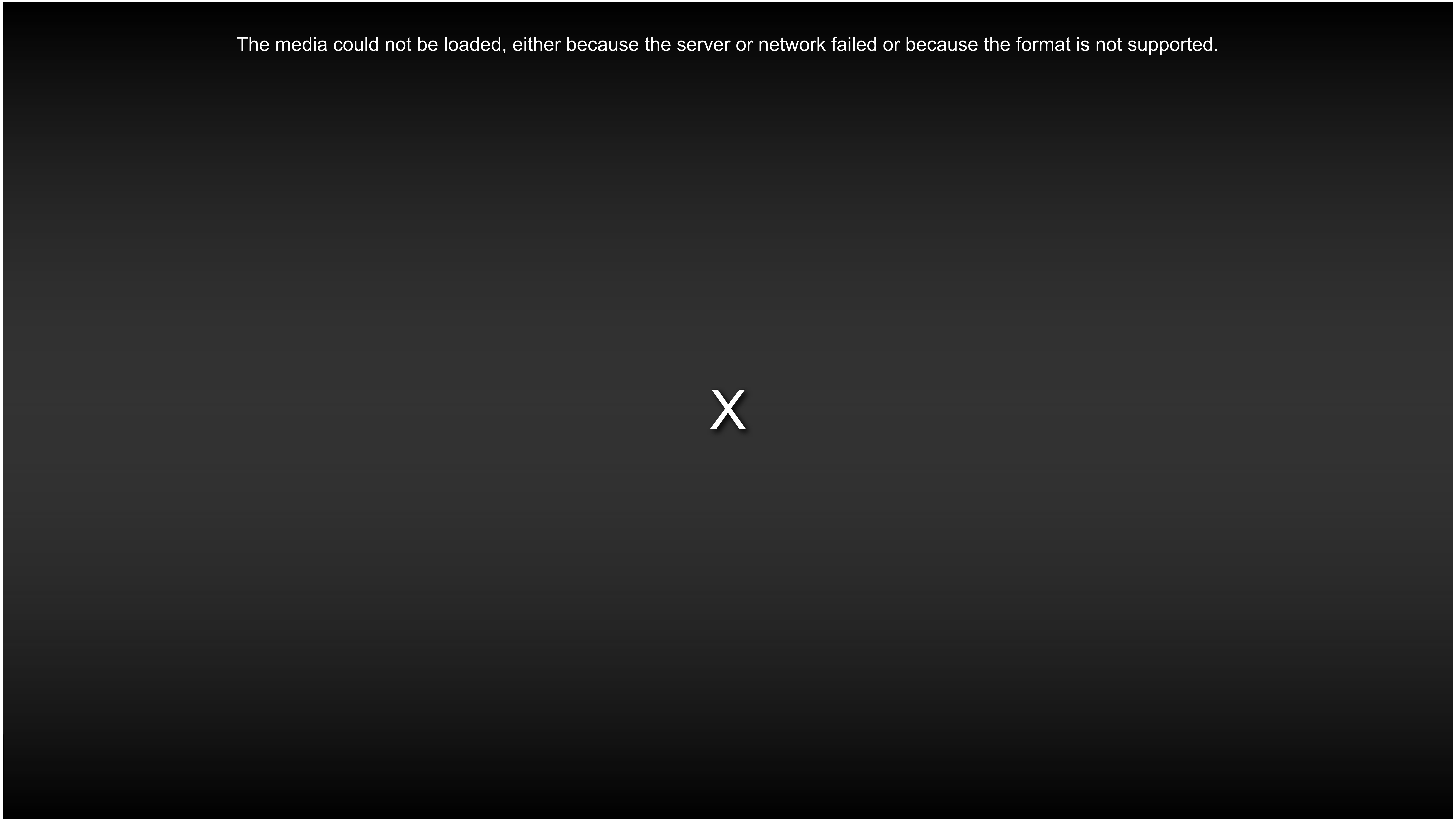
World models

- The sequence of latent representations $\mathbf{z}_0, \dots \mathbf{z}_t$ in a game is fed to a LSTM layer together with the actions a_t to compress what happens over time.
- A **Mixture Density Network** (MDN) is used to predict the **distribution** of the next latent representations $P(\mathbf{z}_{t+1} | a_t, \mathbf{h}_t, \dots \mathbf{z}_t)$.
- The RNN-MDN architecture has been used successfully in the past for sequence generation problems such as generating handwriting and sketches (Sketch-RNN).



https://worldmodels.github.io/

Sketch-RNN



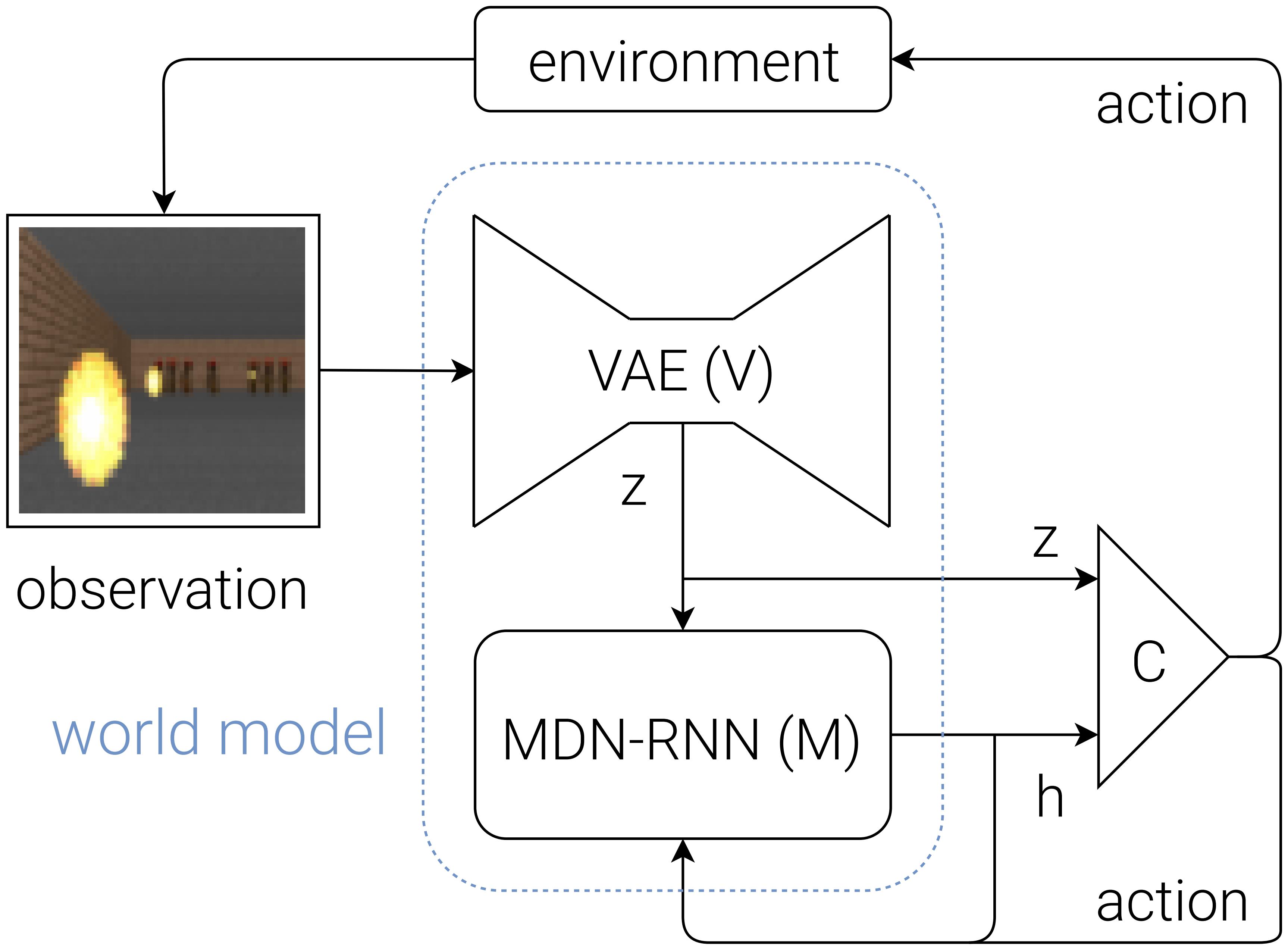
https://magenta.tensorflow.org/sketch-rnn-demo

World models

- The last step is the **controller**. It takes a latent representation $\mathbf{z}_t$ and the current hidden state of the LSTM $\mathbf{h}_t$ as inputs and selects an action **linearly**:

$$a_t = \tanh(W \, [\mathbf{z}_t, \mathbf{h}_t] + b)$$

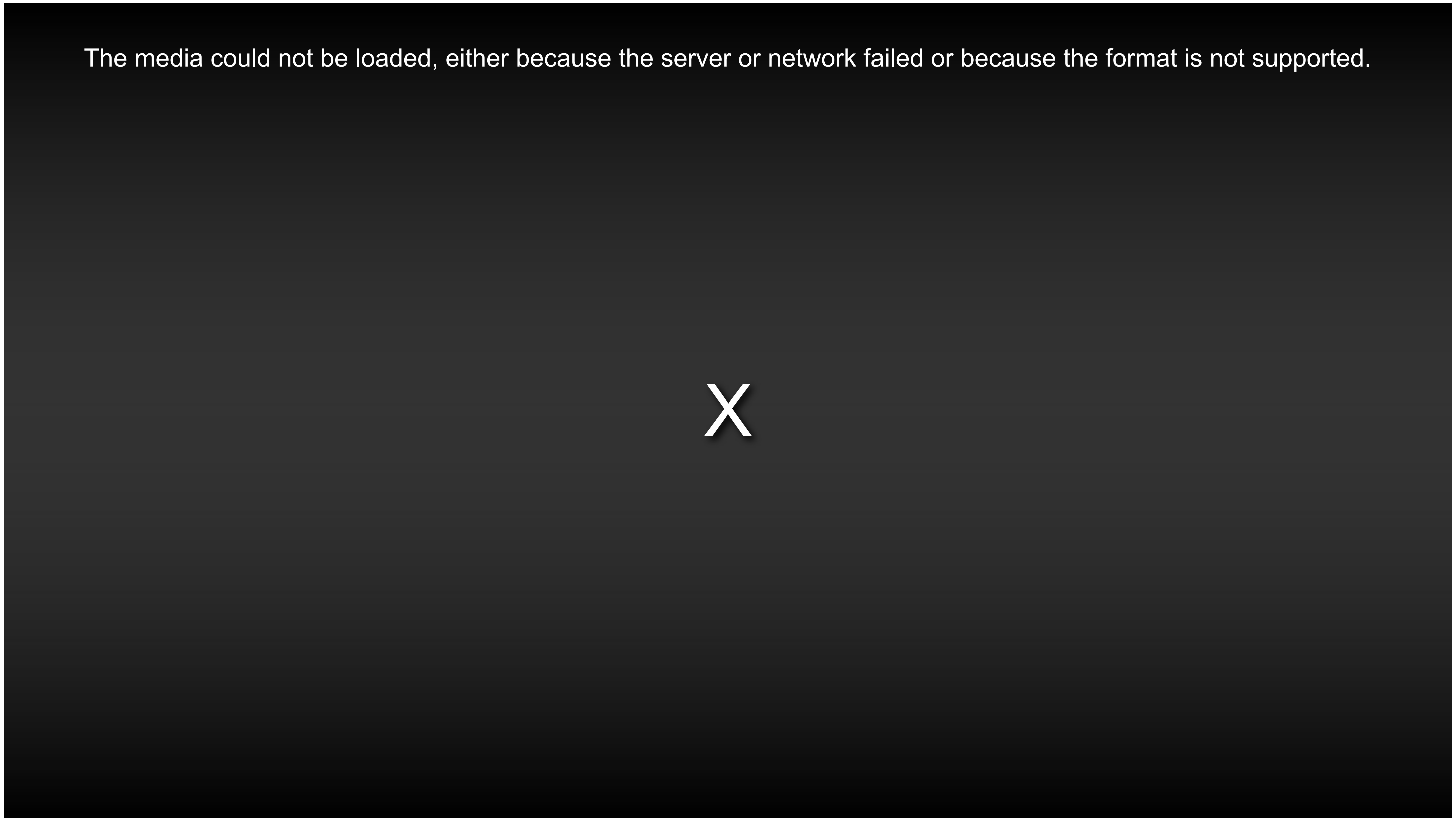
- A RL actor cannot get simpler as that...



https://worldmodels.github.io/

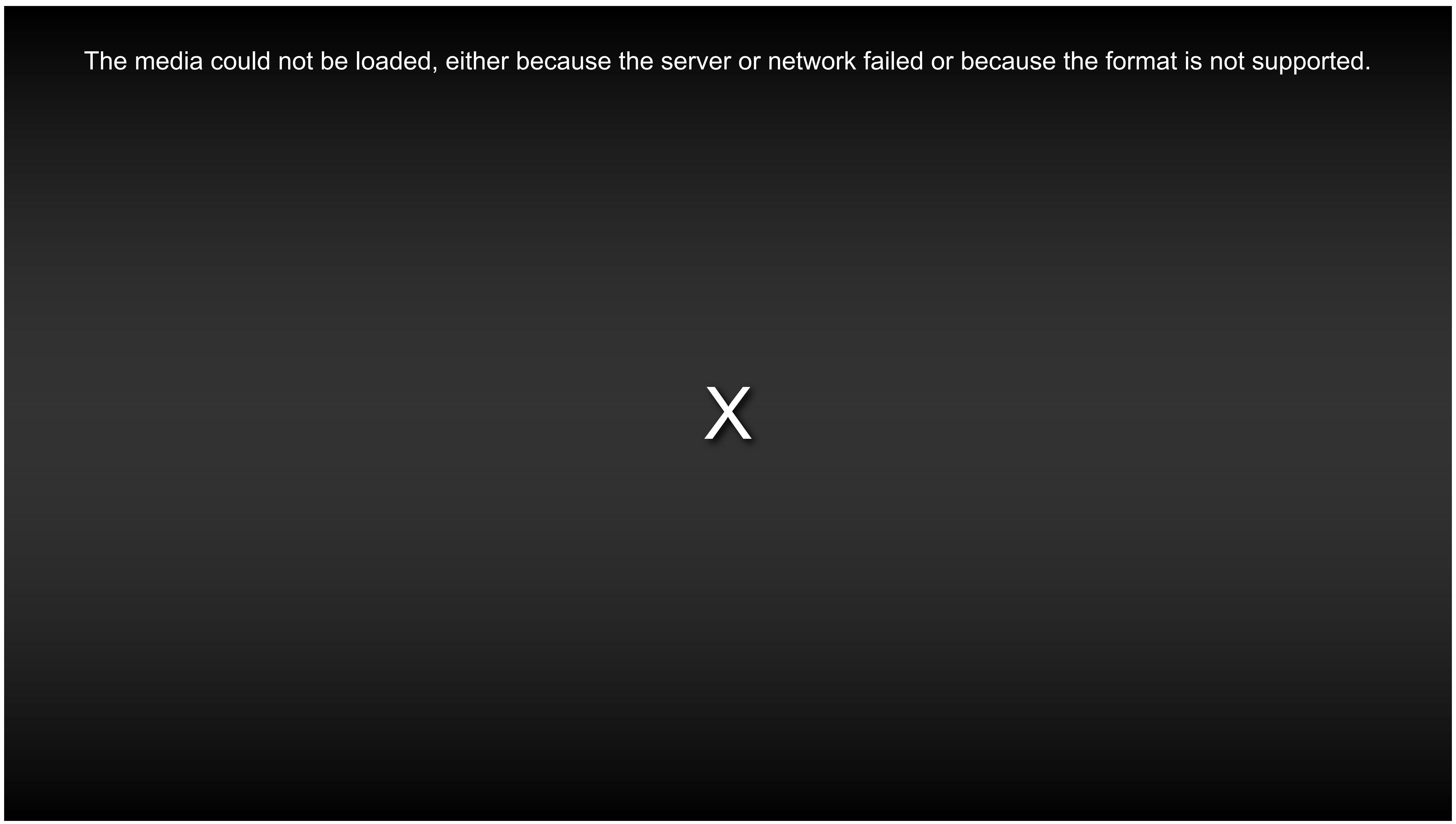
- The controller is not even trained with RL: it uses a genetic algorithm, the Covariance-Matrix Adaptation Evolution Strategy (CMA-ES), to find the output weights that maximize the returns.
- The world model is trained by classical supervised learning using a random agent before learning.

World models : car racing



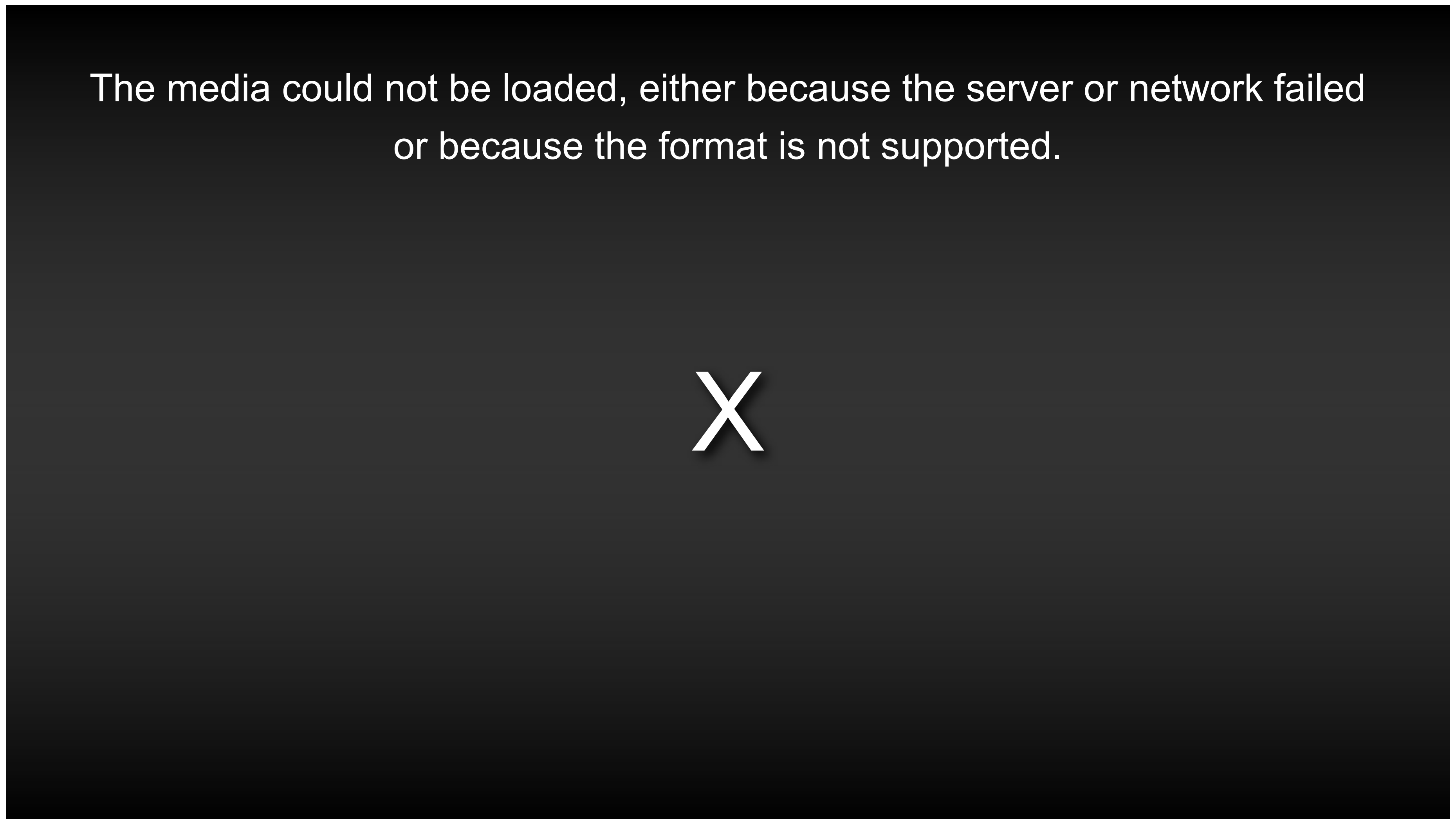
World models : car racing

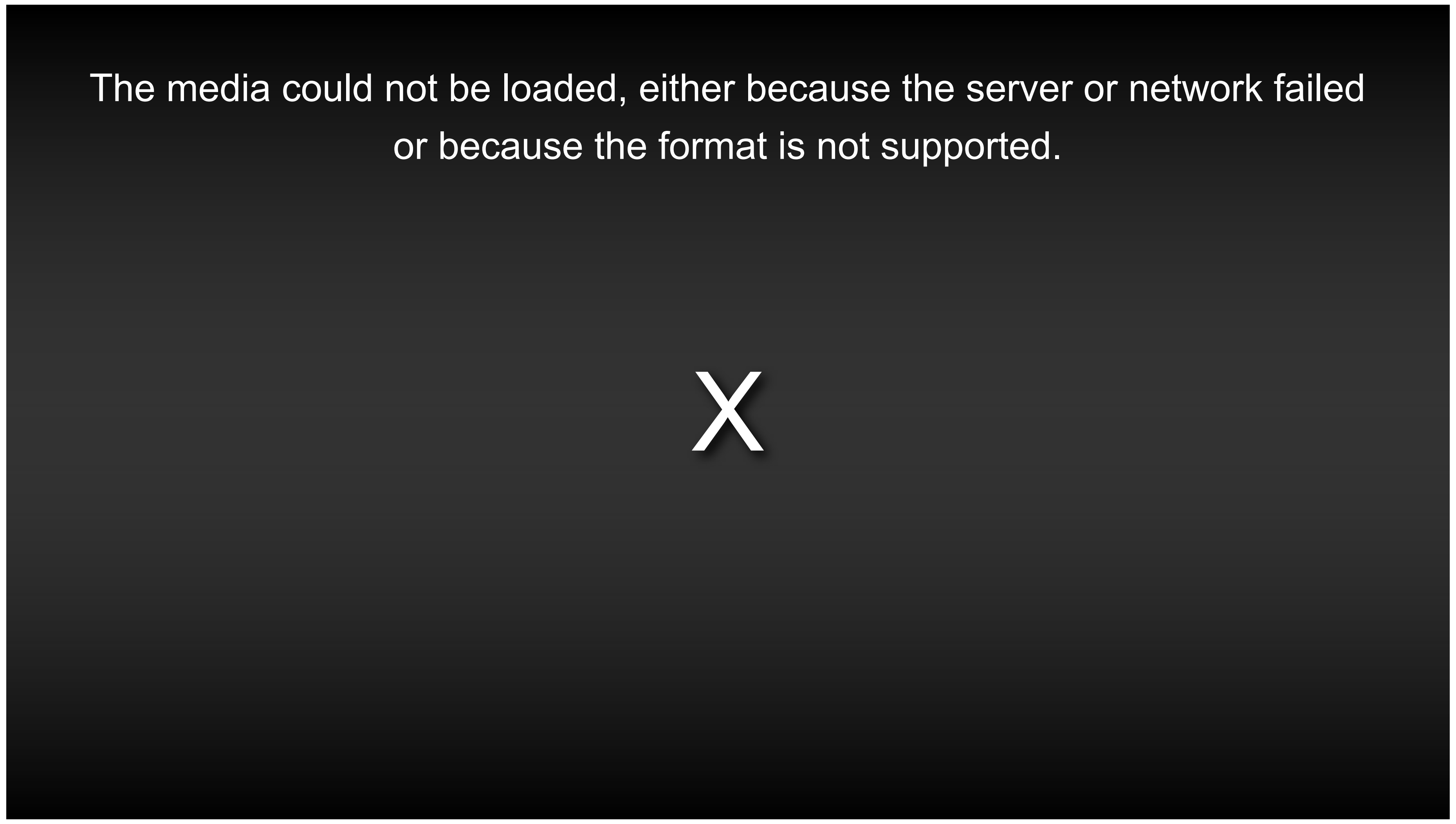
- Below is the input of the VAE and the reconstruction.
- The reconstruction does not have to be perfect as long as the latent space is informative.



World models : car racing

- Controller seeing only $\mathbf{z}_t$.
- Controller seeing both $\mathbf{z}_t$ and $\mathbf{h}_t$.





- Having access to a full rollout of the future leads to more stable driving.

World models

Algorithm:

1. Collect 10,000 rollouts from a random policy.
2. Train VAE (V) to encode each frame into a latent vector $\mathbf{z} \in \mathcal{R}^{32}$.
3. Train MDN-RNN (M) to model $P(\mathbf{z}_{t+1} | a_t, \mathbf{h}_t, \ldots \mathbf{z}_t)$.
4. Evolve Controller (C) to maximize the expected cumulative reward of a rollout.

Parameters for car racing:

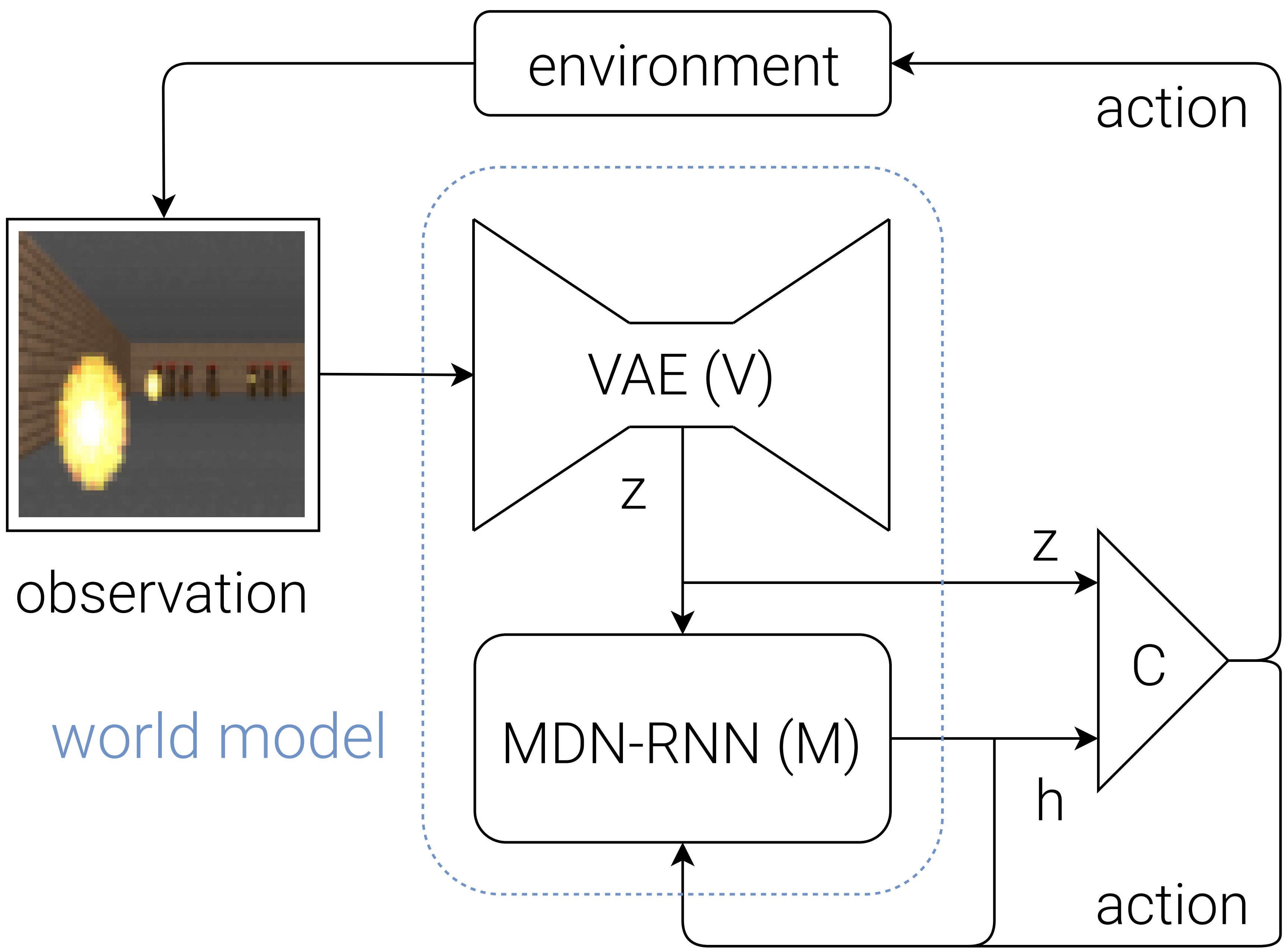
Model	Parameter Count
VAE	4,348,547
MDN-RNN	422,368
Controller	867

World models : car racing

Method	Average Score over 100 Random Tracks
DQN [53]	343 ± 18
A3C (continuous) [52]	591 ± 45
A3C (discrete) [51]	652 ± 10
ceobillionaire's algorithm (unpublished) [47]	838 ± 11
V model only, z input	632 ± 251
V model only, z input with a hidden layer	788 ± 141
Full World Model, z and h	$\mathbf{906 \pm 21}$

https://worldmodels.github.io/

World models



https://worldmodels.github.io/

- The **world model** V+M is learned **offline** with a random agent, using unsupervised learning.
- The **controller** C has few weights (1000) and can be trained by evolutionary algorithms, not even RL.
- The network can even learn by playing entirely in its **own imagination** as the world model can be applied on itself and predict all future frames.
- It just need to additionally predict the reward.
- The learned policy can then be transferred to the real environment.

4 - Deep Planning Network - PlaNet

Learning Latent Dynamics for Planning from Pixels

Danijar Hafner [1 2] **Timothy Lillicrap** [3] **Ian Fischer** [4] **Ruben Villegas** [1 5]
David Ha [1] **Honglak Lee** [1] **James Davidson** [1]

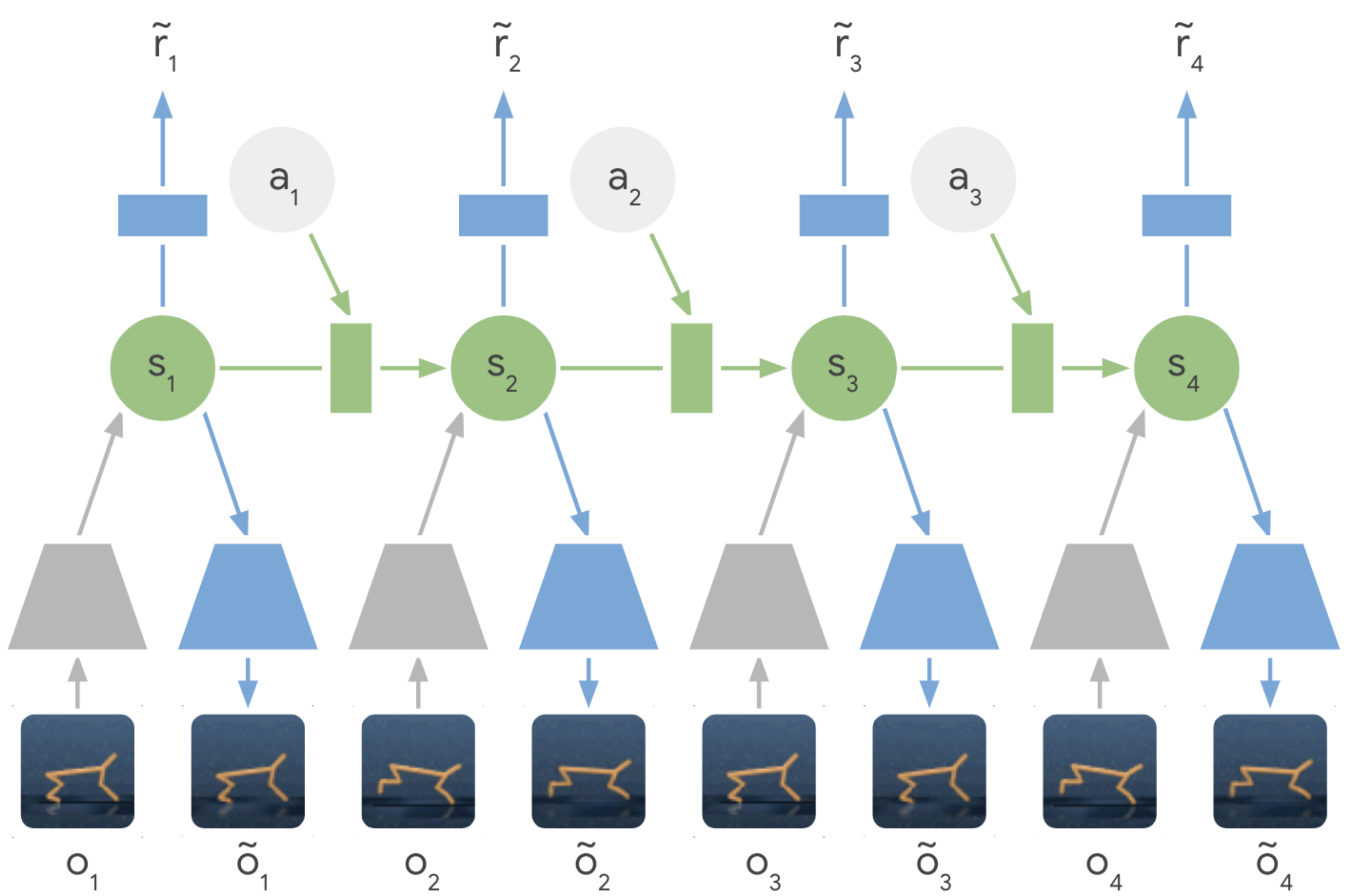
PlaNet

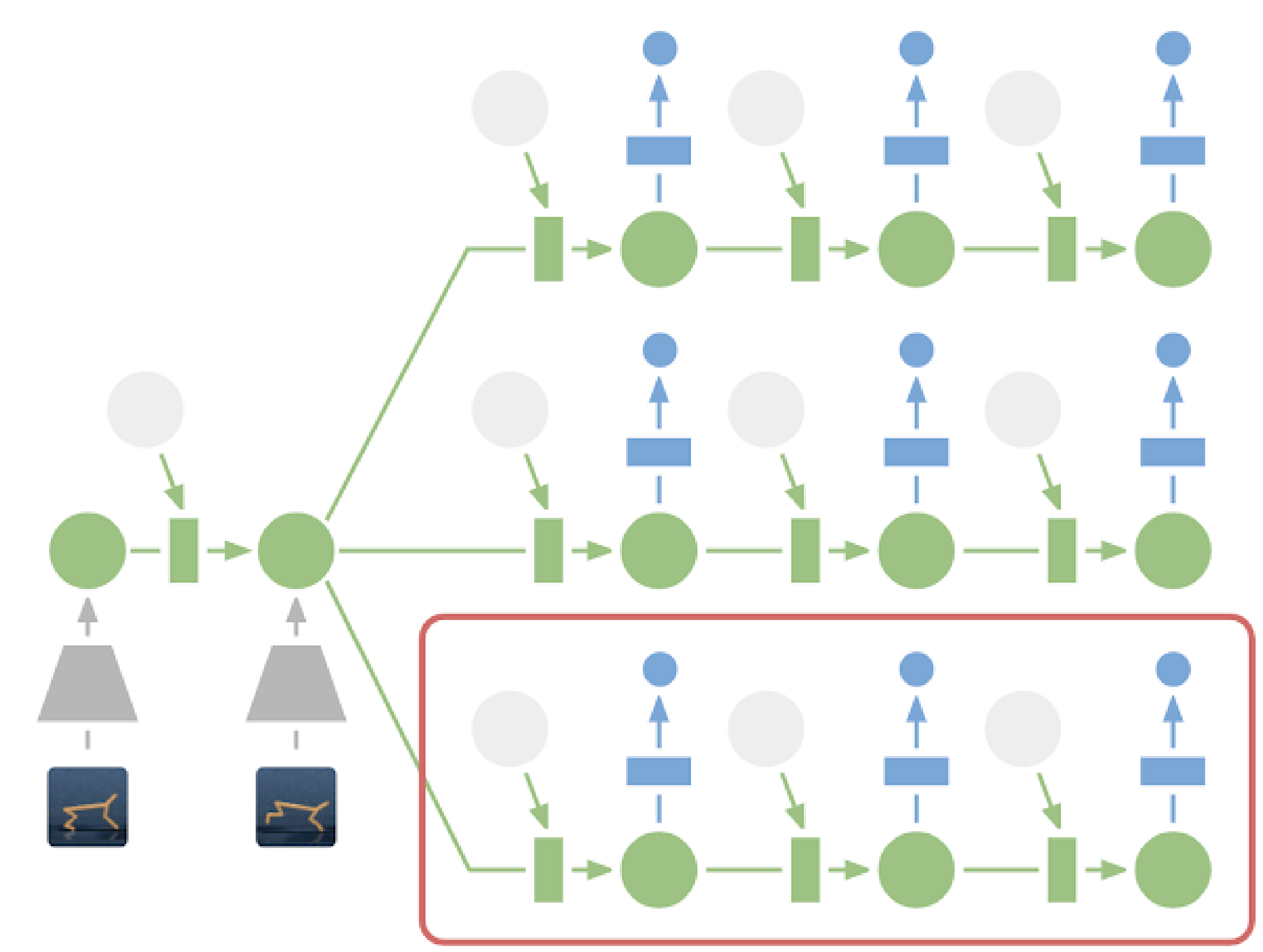
- PlaNet extends the idea of World models by learning the model together with the policy (**end-to-end**).
- It learns a **latent dynamics model** that takes the past observations o_t into account (needed for POMDPs):

$$s_t, r_{t+1}, \hat{o}_t = f(o_t, a_t, s_{t-1})$$

and plans in the latent space using multiple rollouts:

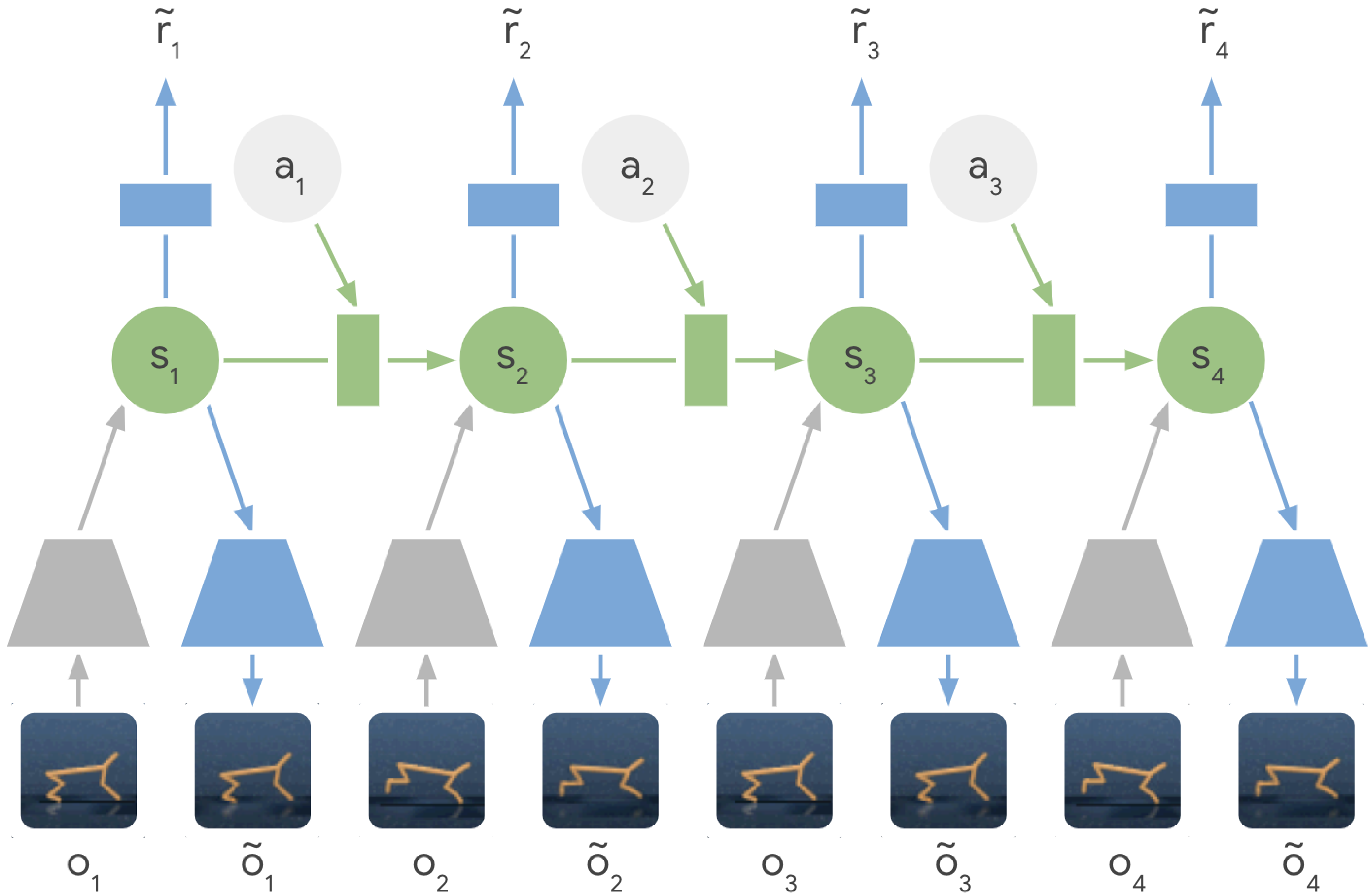
$$a_t = \arg\max_a \mathbb{E}[R(s_t, a, s_{t+1}, \ldots)]$$





Source: https://planetrl.github.io/

PlaNet: latent dynamics model



Source: https://ai.googleblog.com/2019/02/introducing-planet-deep-planning.html

PlaNet: latent dynamics model

- The latent dynamics model is a sequential variational autoencoder learning concurrently:

1. An **encoder** from the observation o_t to the latent space s_t.

$$q(s_t | o_t)$$

2. A **decoder** from the latent space to the reconstructed observation $\hat{o}_t$.

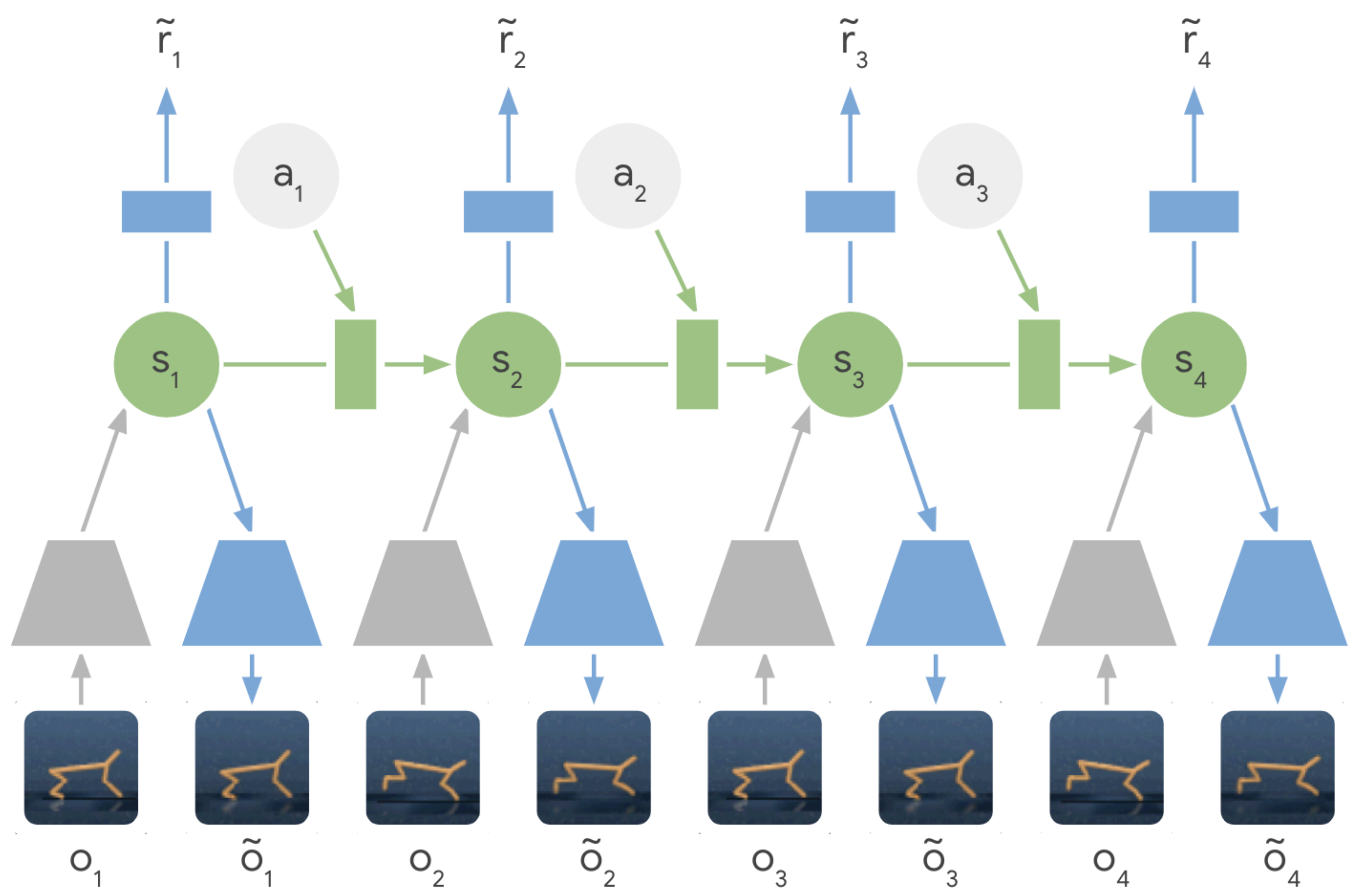
$$p(\hat{o}_t | s_t)$$

3. A **transition model** to predict the next latent representation given an action.

$$p(s_{t+1} | s_t, a_t)$$

4. A **reward model** predicting the immediate reward.

$$p(r_t | s_t)$$



Source: https://ai.googleblog.com/2019/02/introducing-planet-deep-planning.html

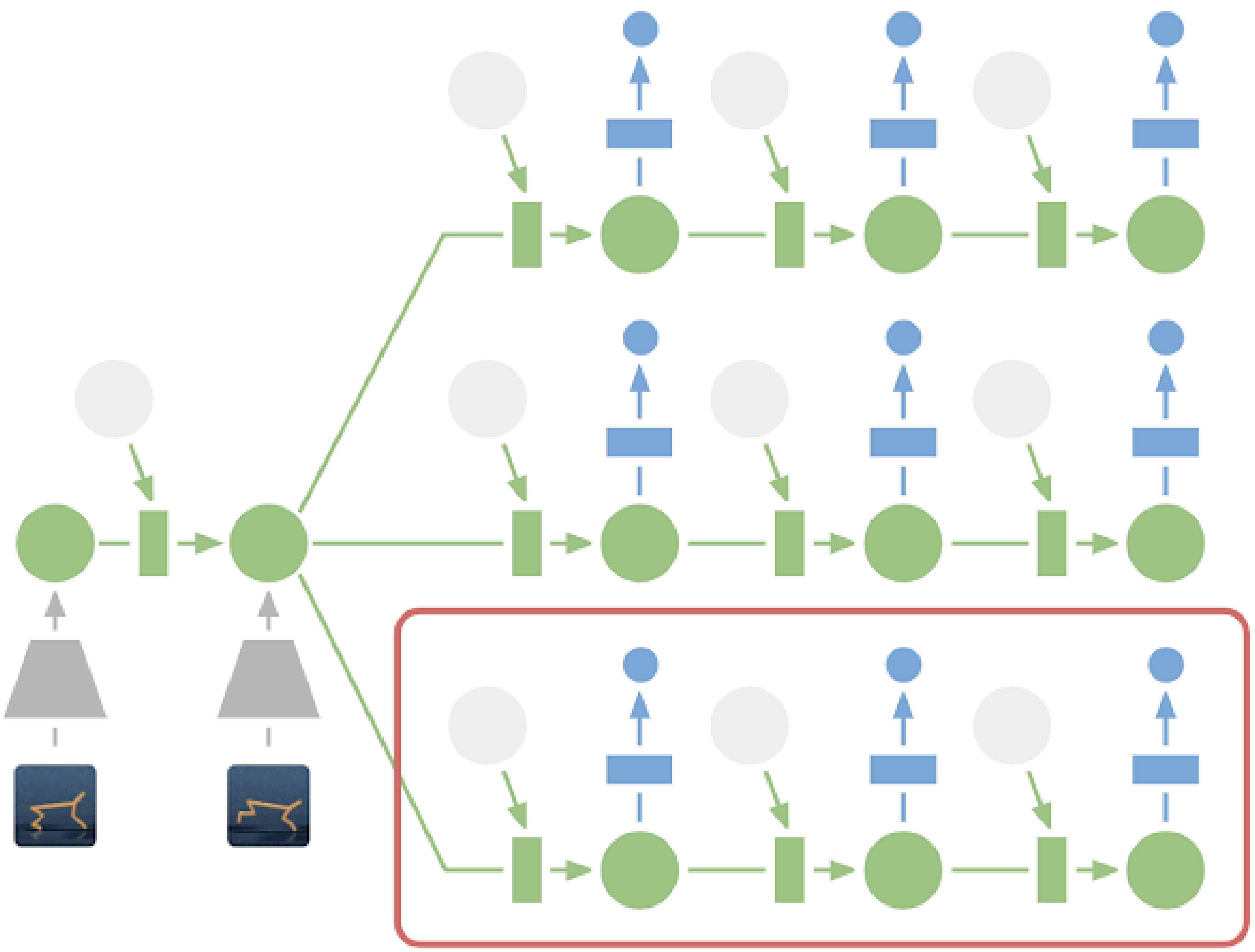
The loss function to train this **recurrent state-space model** (RSSM), with a deterministic component in the

PlaNet: latent dynamics model

- Training sequences $(o_1, a_1, o_2, \ldots, o_T)$ can be generated **off-policy** (e.g. from demonstrations) or on-policy.

Source: https://ai.googleblog.com/2020/03/introducing-dreamer-scalable.html

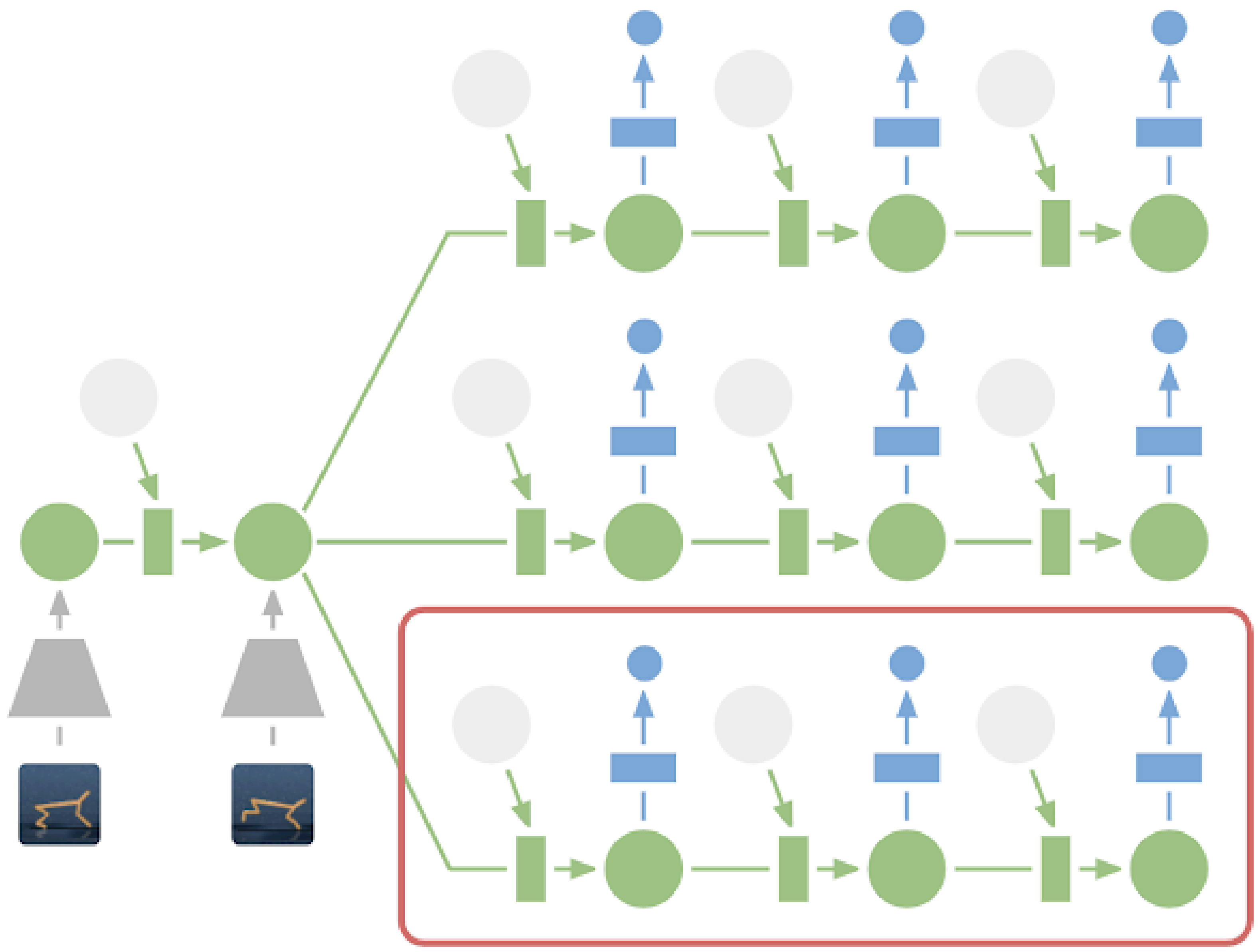
PlaNet: latent space planning



Source: https://ai.googleblog.com/2019/02/introducing-planet-deep-planning.html

PlaNet: latent space planning

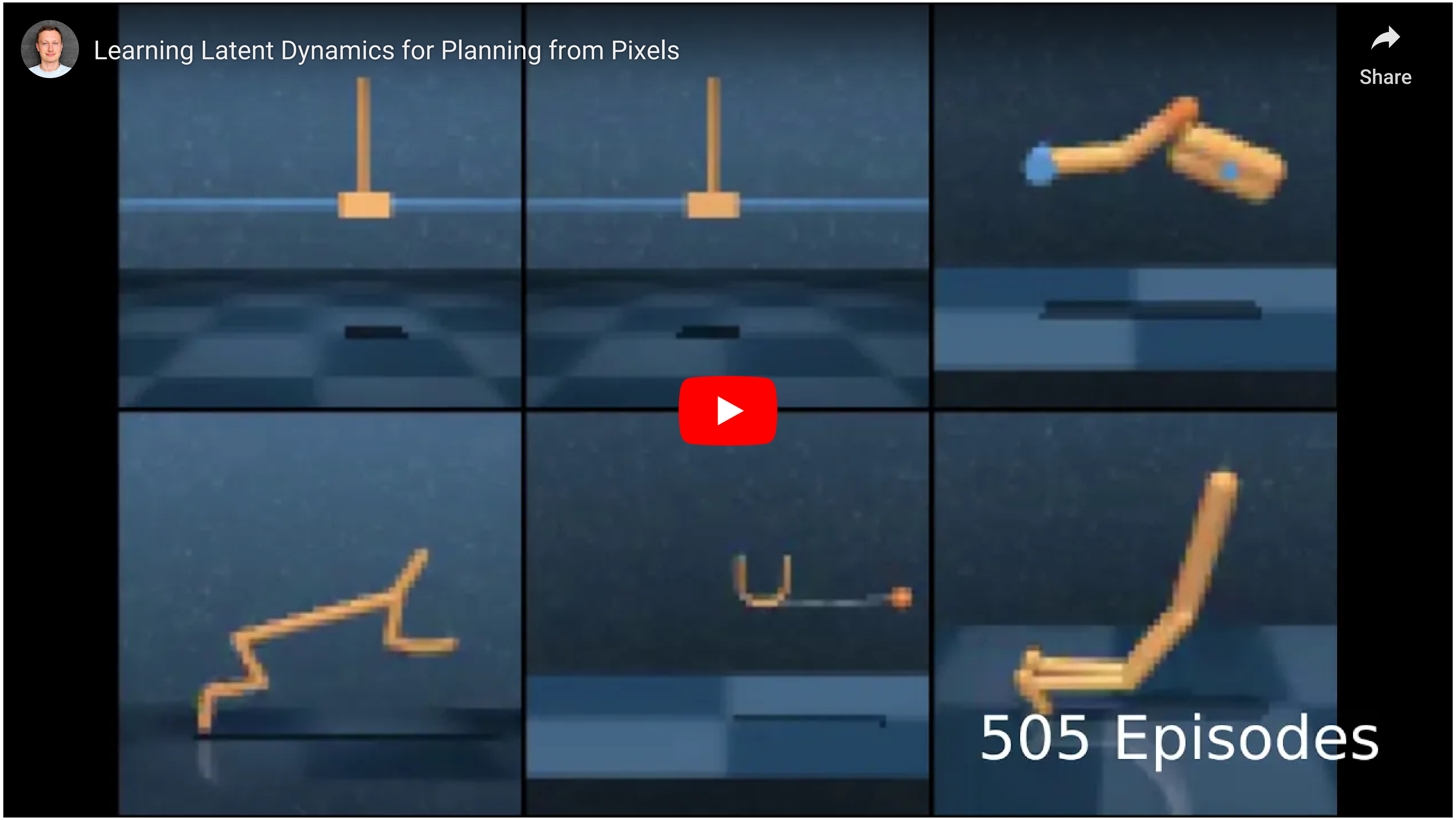
- From a single observation o_t encoded into s_t, 10000 rollouts are generated using **random sampling**.
- A belief over action sequences is updated using the **cross-entropy method** (CEM) in order to restrict the search.
- The first action of the sequence with the highest estimated return (reward model) is executed.
- At the next time step, planning starts from scratch: Model Predictive Control.
- There is no actor in PlaNet, only a transition model used for planning.



Source: https://ai.googleblog.com/2019/02/introducing-planet-deep-planning.html

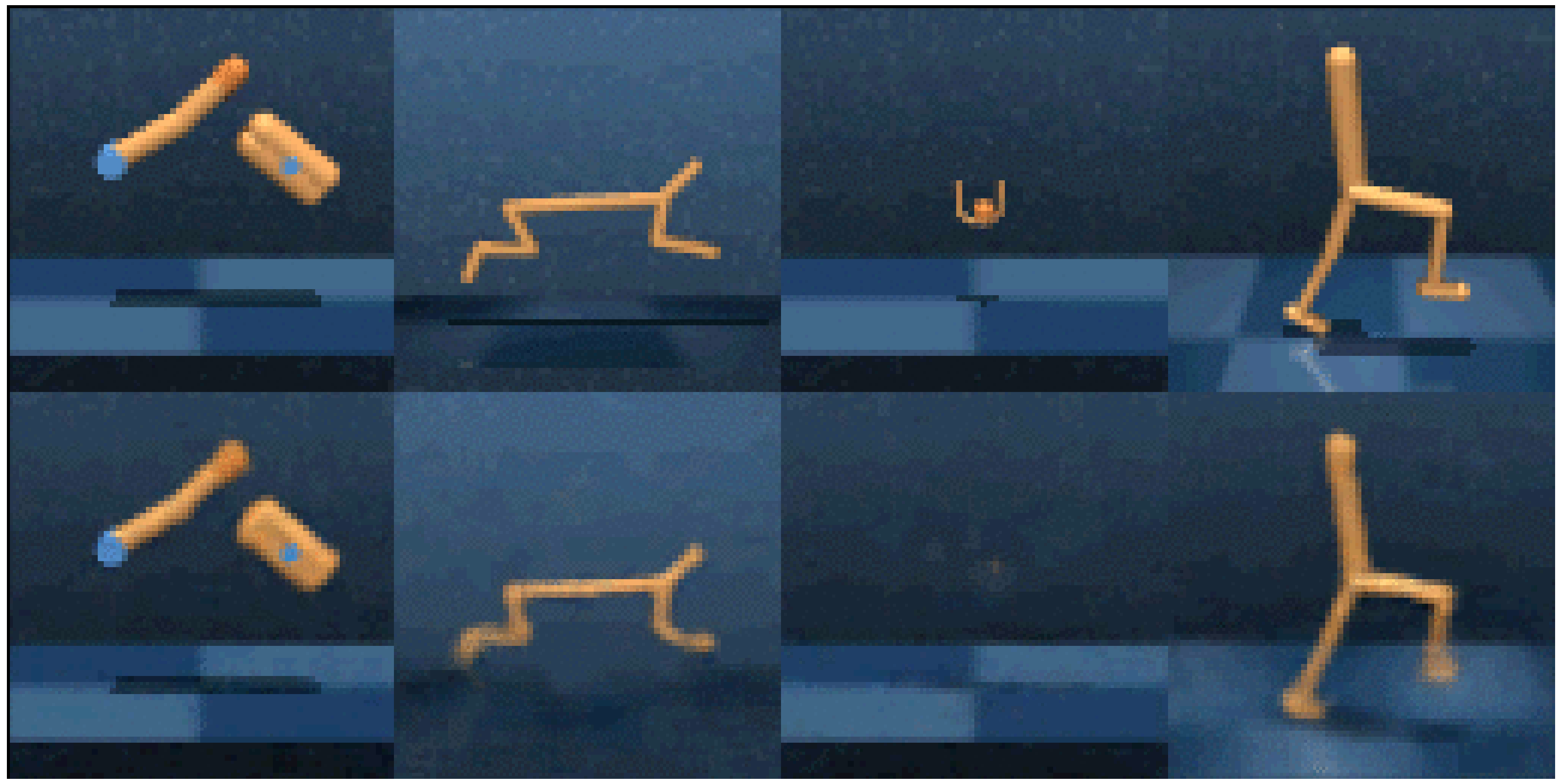
PlaNet results

- Planet learns continuous image-based control problems in 2000 episodes, where D4PG needs 50 times more.



PlaNet results

- The latent dynamics model can learn 6 control tasks **at the same time**.
- As there is no actor, but only a planner, the same network can control all agents!



Source: https://ai.googleblog.com/2019/02/introducing-planet-deep-planning.html

5 - Dreamer

Published as a conference paper at ICLR 2020

DREAM TO CONTROL: LEARNING BEHAVIORS BY LATENT IMAGINATION

Danijar Hafner *
University of Toronto
Google Brain

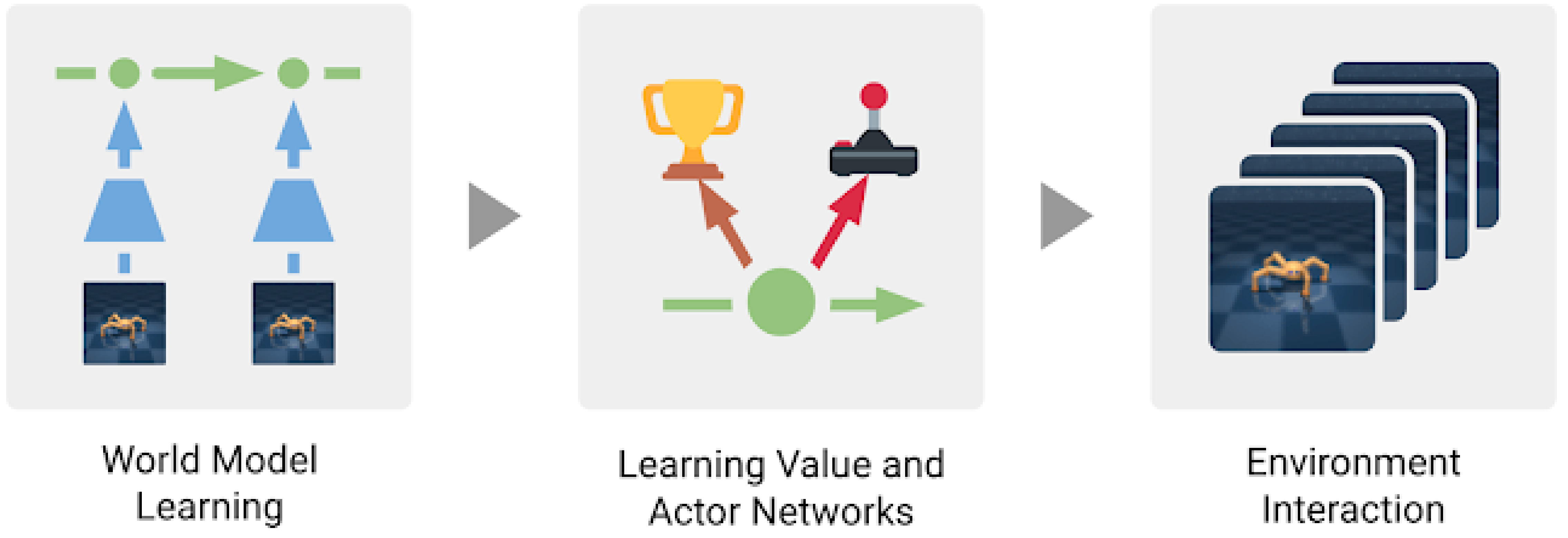
Timothy Lillicrap
DeepMind

Jimmy Ba
University of Toronto

Mohammad Norouzi
Google Brain

Dreamer

- Dreamer extends the idea of PlaNet by additionally **training an actor** instead of using a MPC planner.
- The latent dynamics model is the same RSSM architecture.
- Training a “model-free” actor on imaginary rollouts instead of MPC planning should reduce the computational time.



Source: https://ai.googleblog.com/2020/03/introducing-dreamer-scalable.html

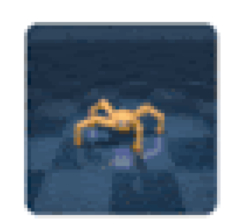
Dreamer: latent dynamics model

- The latent dynamics model is the same as in PlaNet, learning from past experiences.

Source: https://ai.googleblog.com/2020/03/introducing-dreamer-scalable.html

Dreamer: behavior module

- The behavior module learns to predict the value of a state $V_\varphi(s)$ and the policy $\pi_\theta(s)$ (actor-critic).
- It is trained **in imagination** in the latent space using the reward model for the immediate rewards (to compute returns) and the transition model for the next states.



o_1

Source: https://ai.googleblog.com/2020/03/introducing-dreamer-scalable.html

- The current observation o_t is encoded into a state s_t, the actor selects an action a_t, the transition model predicts s_{t+1}, the reward model predicts r_{t+1}, the critic predicts $V_\varphi(s_t)$.
- At the end of the sequence, we apply **backpropagation-through-time** to train the actor and the critic.

Dreamer: behavior module

- The **critic** $V_\varphi(s_t)$ is trained on the imaginary sequence $(s_t, a_t, r_{t+1}, s_{t+1}, \ldots, s_T)$ to minimize the prediction error with the λ-return:

$$R^\lambda_t = (1 - \lambda) \sum_{n=1}^{T-t-1} \lambda^{n-1} \, R^n_t + \lambda^{T-t-1} \, R_t$$

- The **actor** $\pi_\theta(s_t, a_t)$ is trained on the sequence to maximize the sum of the value of the future states:

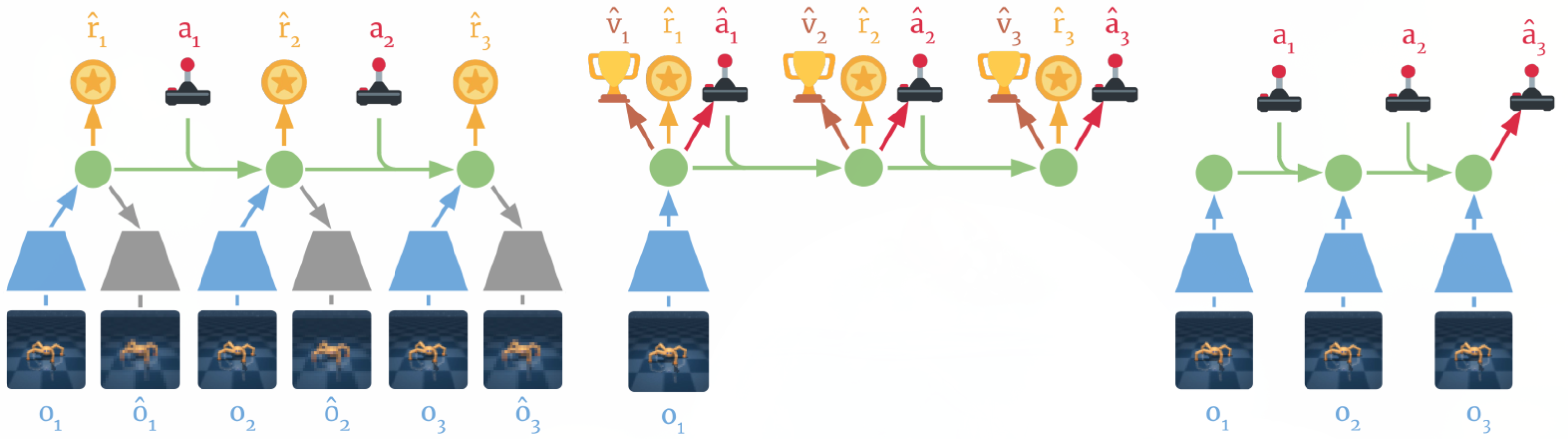
$$\mathcal{J}(\theta) = \mathbb{E}_{s_t, a_t \sim \pi_\theta} [\sum_{t'=t}^T V_\varphi(s_{t'})]$$

o_1

Source: https://ai.googleblog.com/2020/03/introducing-dreamer-scalable.html

Dreamer

- The main advantage of training an actor is that we need only one rollout when training it: backpropagation maximizes the expected returns.
- When acting, we just need to encode the history of the episode in the latent space, and the actor becomes model-free!



(a) Learn dynamics from experience (b) Learn behavior in imagination (c) Act in the environment

Dreamer results

- Dreamer beats model-free and model-based methods on 20 continuous control tasks.

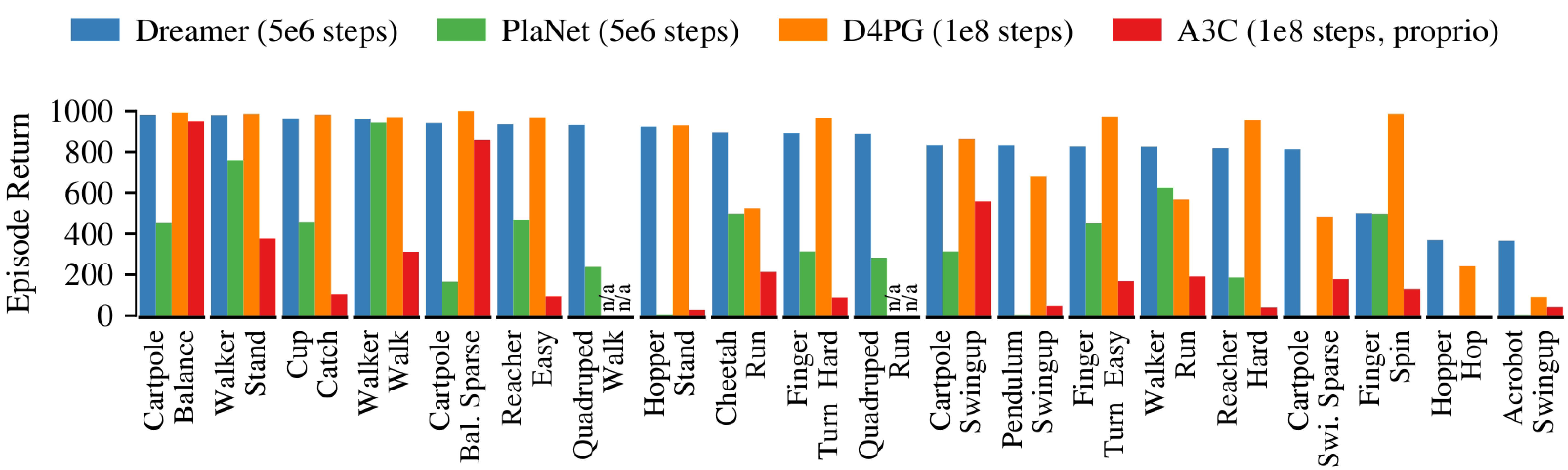
Sparse Cartpole

Acrobot Swingup

Hopper Hop

Walker Run

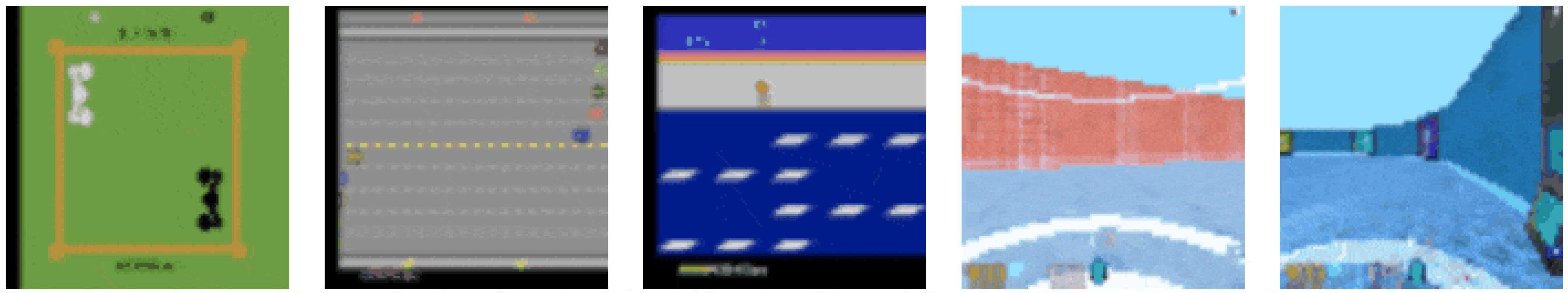
Quadruped Run



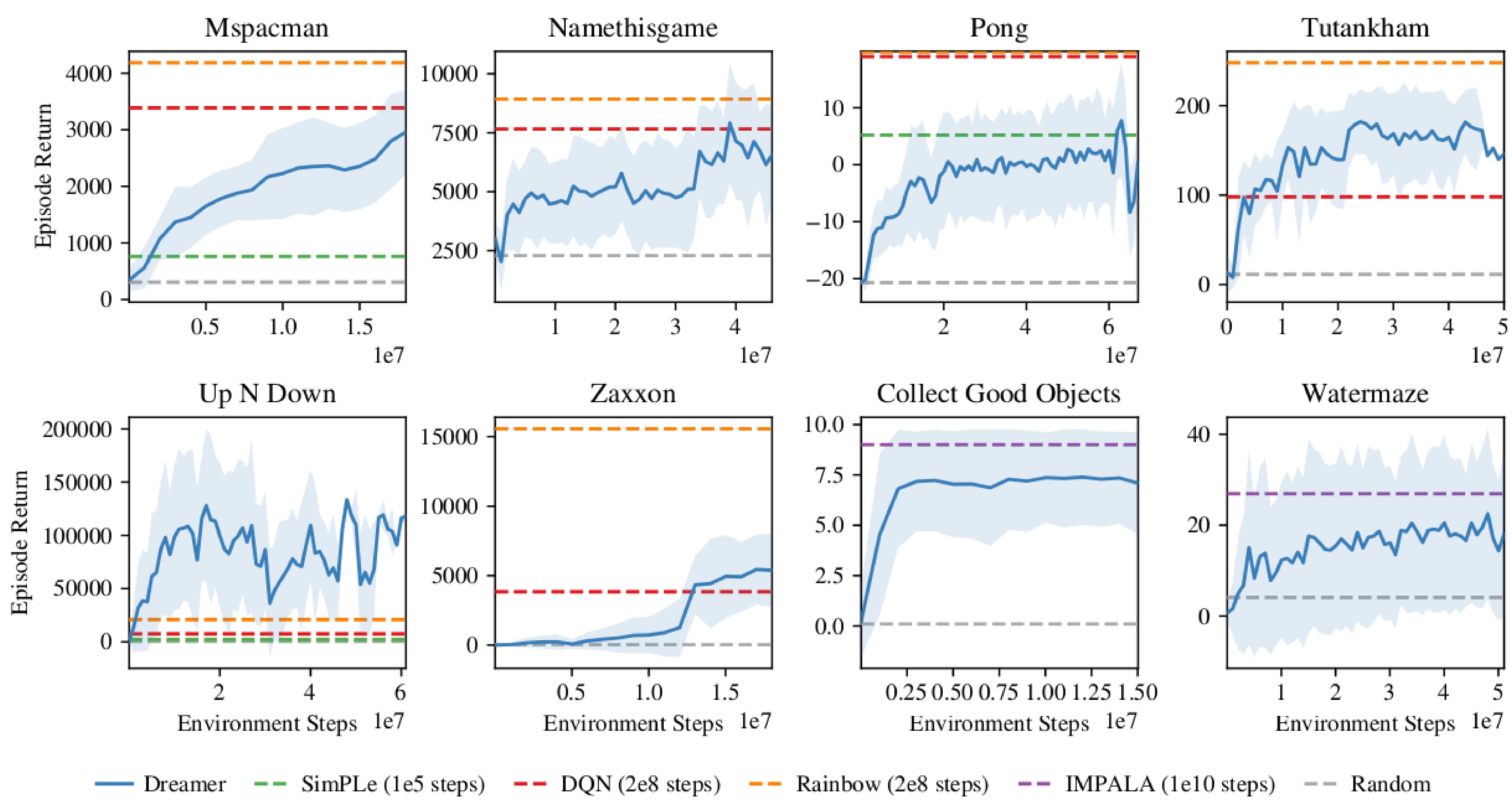
Source: https://ai.googleblog.com/2020/03/introducing-dreamer-scalable.html

Dreamer results

- It also learns Atari and Deepmind lab video games, sometimes on par with Rainbow or IMPALA!



Boxing Freeway Frostbite Collect Objects Watermaze

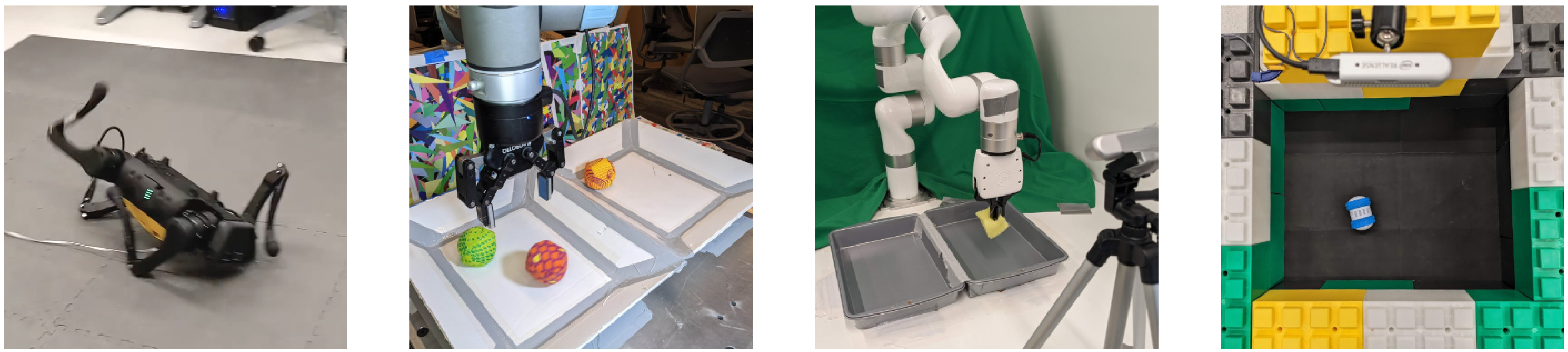


Source: https://dreamrl.github.io/

DayDreamer

- A recent extension of Dreamer, DayDreamer, allows physical robots to learn complex tasks in a few hours.

https://danijar.com/daydreamer



(a) A1 Quadruped Walking (b) UR5 Visual Pick Place (c) XArm Visual Pick Place (d) Sphero Navigation

Figure 1: To study the applicability of Dreamer for sample-efficient robot learning, we apply the algorithm to learn robot locomotion, manipulation, and navigation tasks from scratch in the real world on 4 robots, without simulators. The tasks evaluate a diverse range of challenges, including continuous and discrete actions, dense and sparse rewards, proprioceptive and camera inputs, as well as sensor fusion of multiple input modalities. Learning successfully using the same hyperparameters across all experiments, Dreamer establishes a strong baseline for real world robot learning.

DayDreamer


Learning to Walk in the Real World in 1 Hour (No Simulator)
Share

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