UNIVERSITY OF TECHNOLOGY
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CHEMNITZ

Deep Reinforcement Learning

Planning with learned world models

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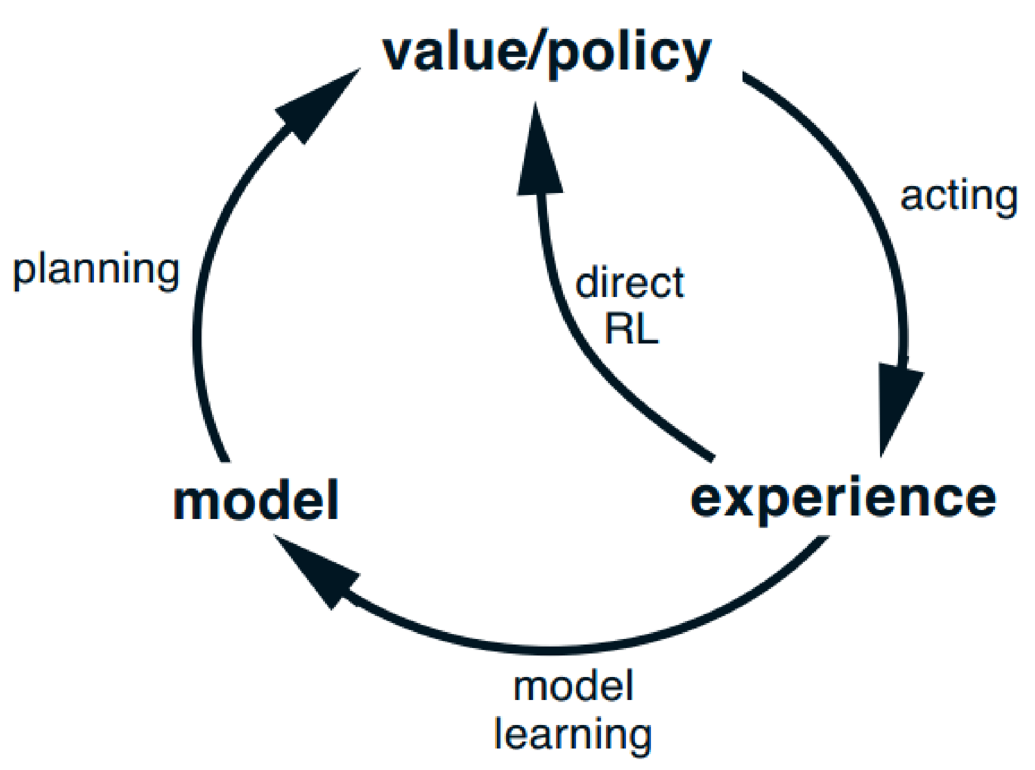
Model-based RL algorithms with learned models

Model-based augmented model-free (MBMF)

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

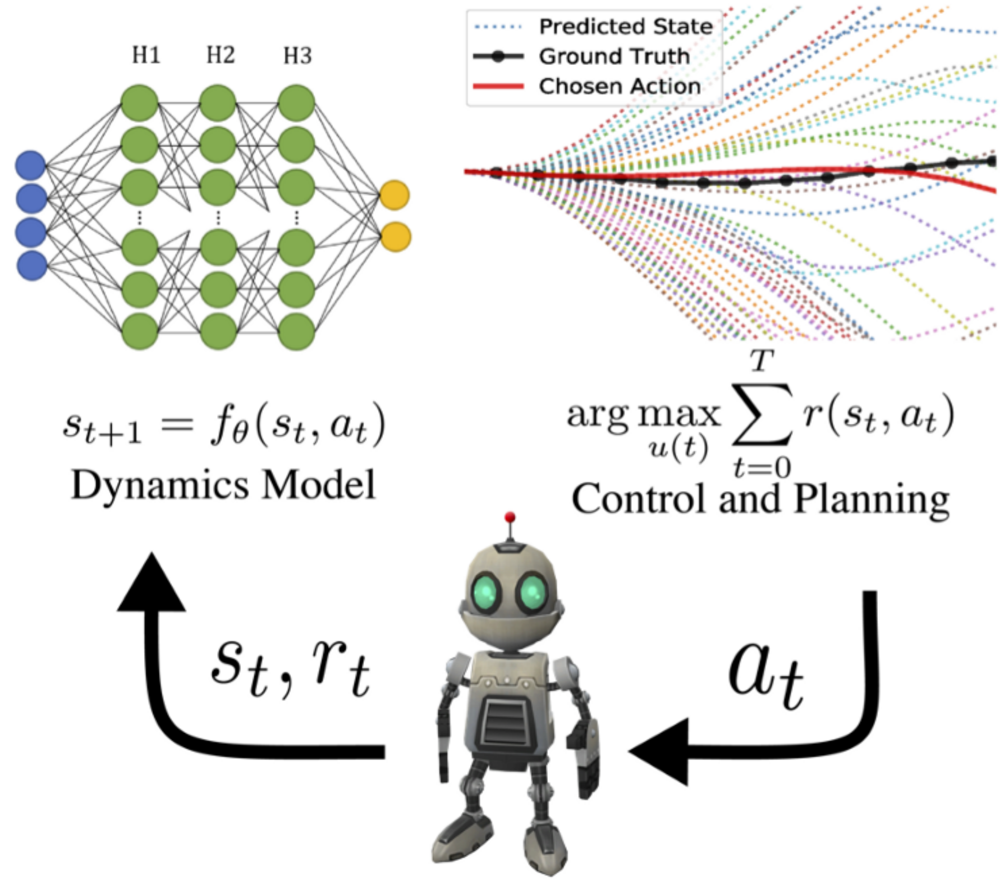


Source: Sutton and Barto (1998)

- 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.

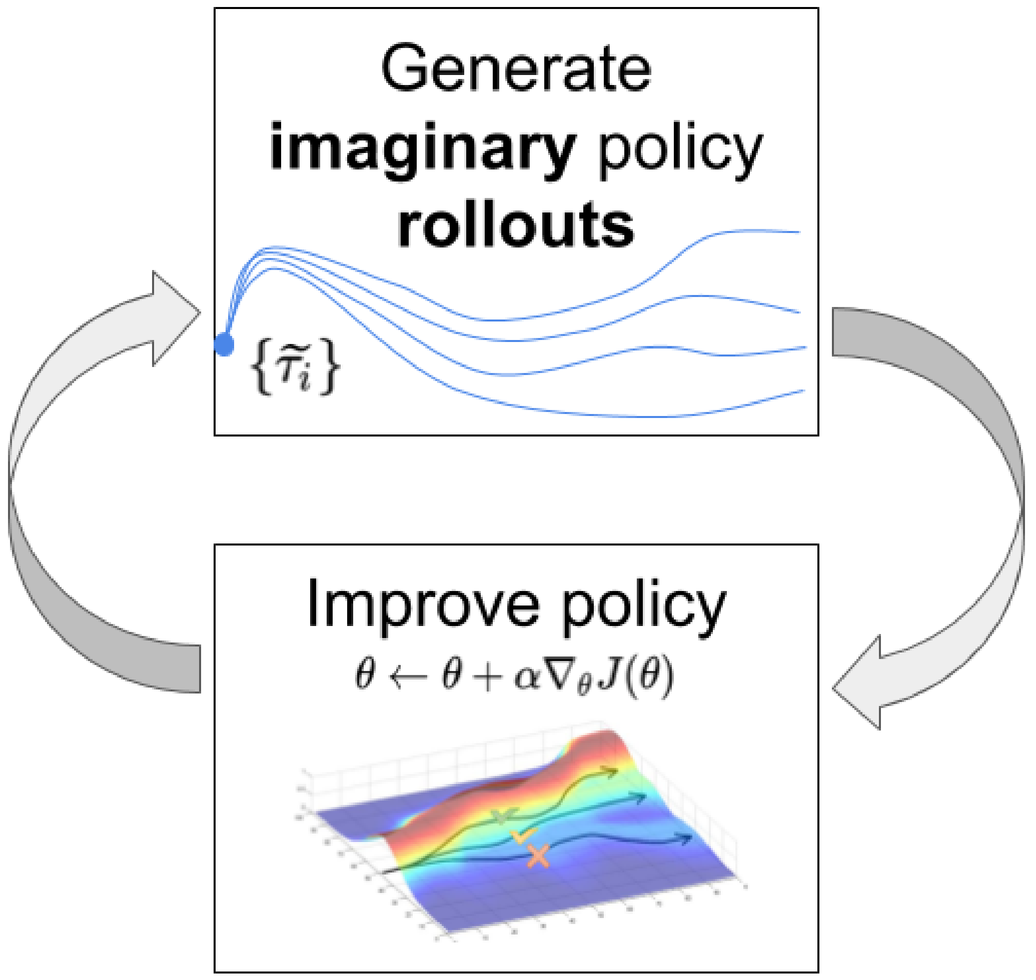


Source: https://arxiv.org/abs/1901.03737

- 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 - Model predictive control (MPC)

Learning from imaginary rollouts



- With a good transition model, you can generate **rollouts**, i.e. imaginary trajectories / episodes using the model.
- Given an initial state s_0 and a policy π, you can unroll the future using the model $s', r = M(s, a)$.

$$\tau = s_0 \xrightarrow[\pi]{} a_0 \xrightarrow[M]{} s_1 \xrightarrow[\pi]{} a_1 \xrightarrow[\pi]{} s_2 \xrightarrow[]{} \ldots \xrightarrow[M]{} s_T$$

- You can then feed these trajectories to any optimizer (classical or model-free RL algorithm) that will learn to maximize the returns.

Training in imagination

1. Collect transitions (s, a, r, s') using a (random/expert) policy b and create a dataset $\mathcal{D} = \{(s_k, a_k, r_, s'_k\}_k$.
2. Train the model $M(s, a) = (s', r)$ on $\mathcal{D}$ using supervised learning.
3. Optimize the policy π on rollouts τ generated by the model.

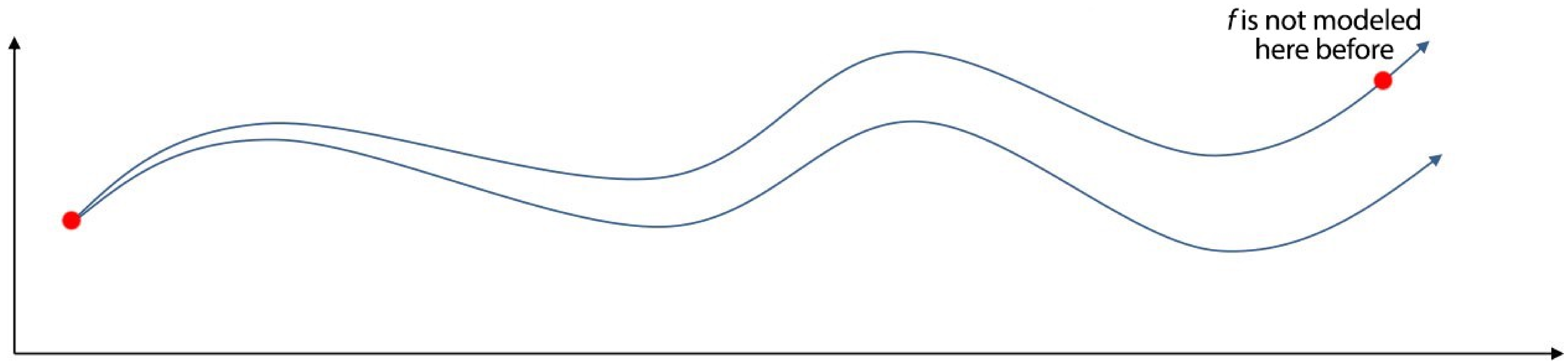
$$\mathcal{J}(\theta) = \mathbb{E}_\tau[R(\tau)]$$

- The only sample complexity is the one needed to train the model: the rest is **emulated**.

Kurutach et al. (2018) Model-Ensemble Trust-Region Policy Optimization. arXiv:1802.10592.

Imperfect model

- For long horizons, the slightest imperfection in the model can accumulate (**drift**) and lead to completely wrong trajectories.

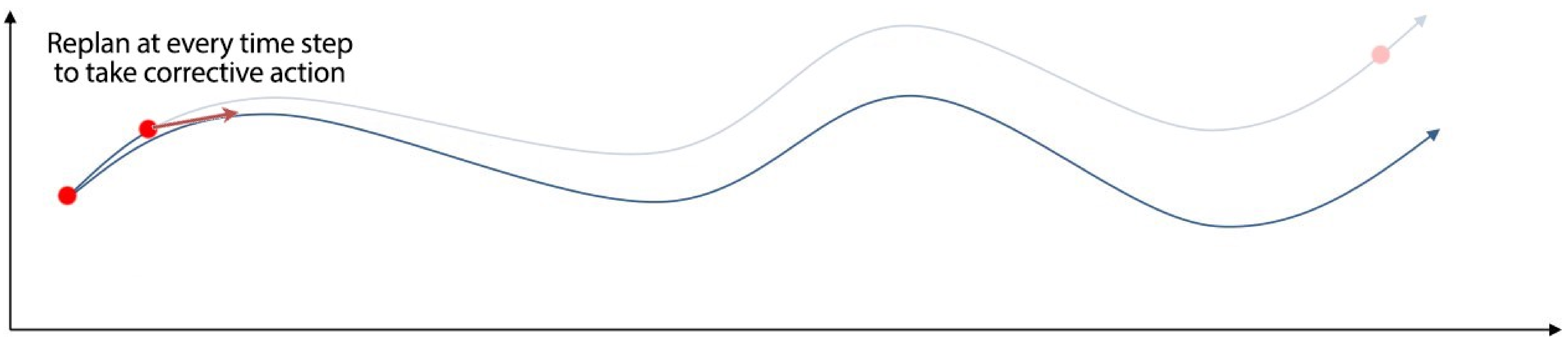


Source: https://medium.com/@jonathan_hui/rl-model-based-reinforcement-learning-3c2b6f0aa323

- The emulated trajectory will have a biased return, the algorithm does not converge to the optimal policy.
- If you have a perfect model, you should not be using RL anyway, as classical control methods would be much faster (but see AlphaGo).

MPC - Model Predictive Control

- The solution is to **replan** at each time step and execute only the first planned action **in the real environment**.



Source: https://medium.com/@jonathan_hui/rl-model-based-reinforcement-learning-3c2b6f0aa323

- Replanning avoids accumulating errors over long horizons.

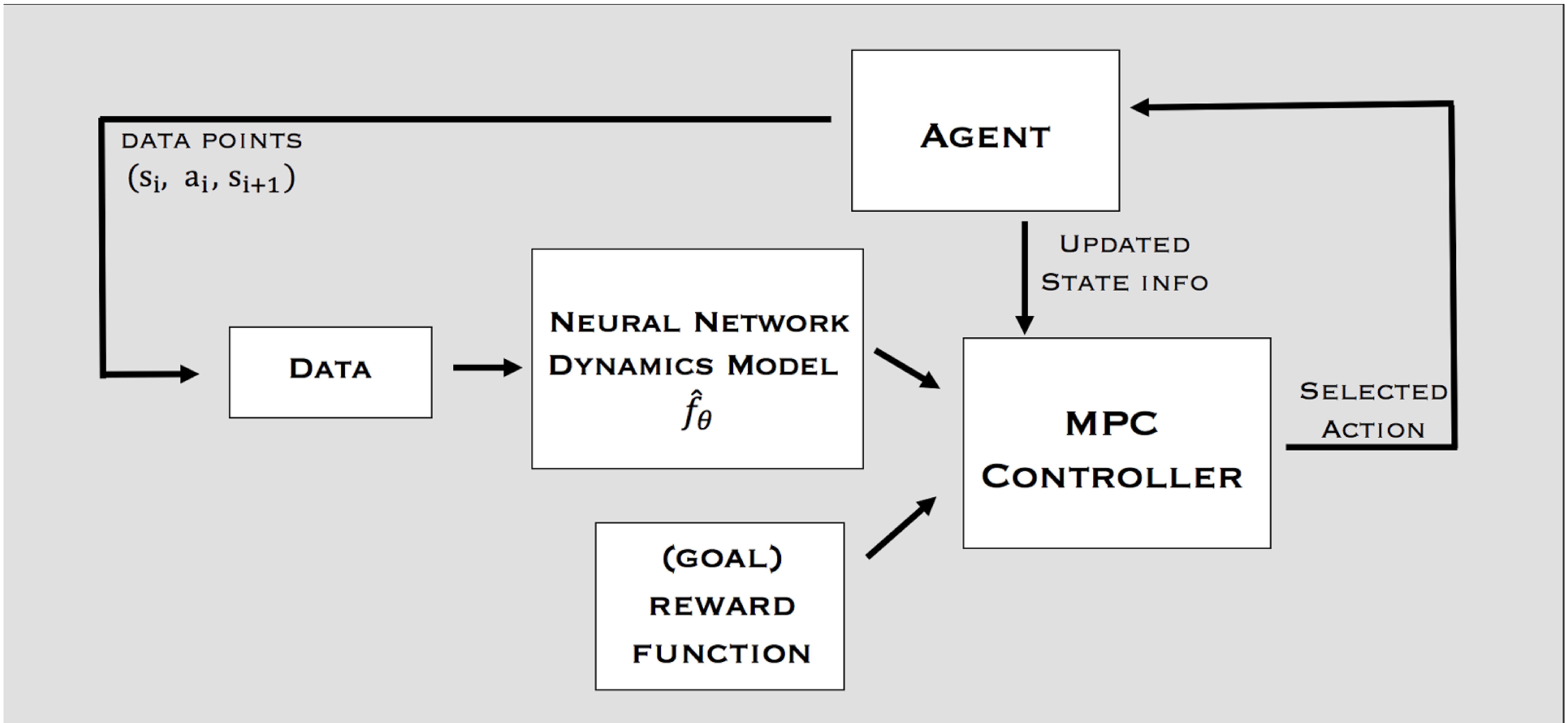
MPC - Model Predictive Control

- Collect transitions (s, a, r, s') using a (random/expert) policy b and create an initial dataset $\mathcal{D} = \{(s_k, a_k, r_, s'_k\}_k$.
- **while** not converged:
  - (Re)Train the dynamics model $M(s, a) = (s', r)$ on $\mathcal{D}$ using supervised learning.
  - **foreach** step t in the trajectory:
    - Plan a trajectory from the current state s_t using the model M, returning a sequence of planned actions:

$$a_t, a_{t+1}, \ldots, a_T$$

    - Take the first action a_t, observe the next state s_{t+1}.
    - Append the transition (s_t, a_t, s_{t+1}) to the dataset.

MPC - Example with a neural model

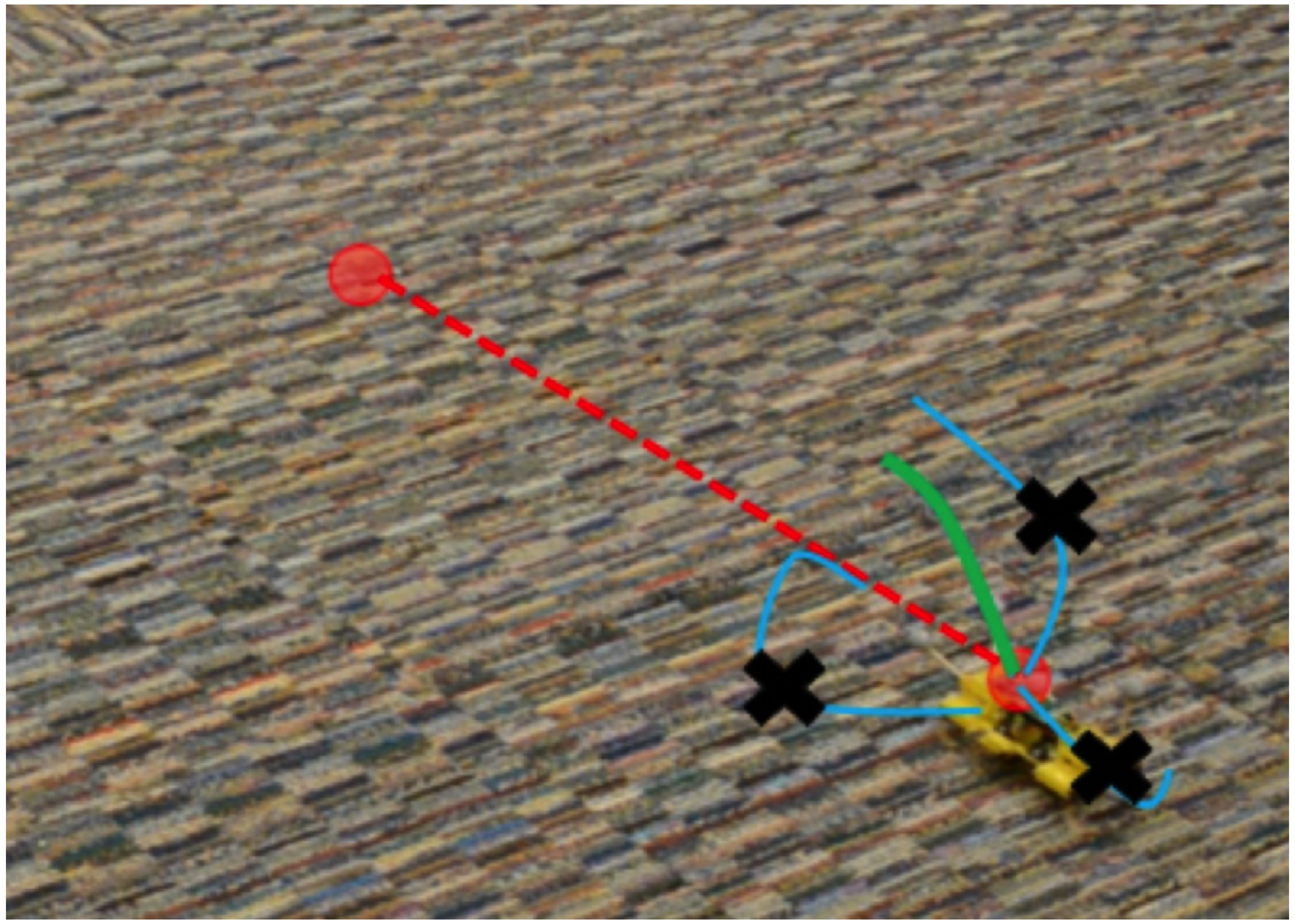


Nagabandi et al. (2017). Neural Network Dynamics for Model-Based Deep Reinforcement Learning with Model-Free Fine-Tuning. arXiv:1708.02596.

MPC - Example with a neural model

- The planner can actually be anything, it does not have to be a RL algorithm. Examples:
- **iLQR** (Iterative Linear Quadratic Regulator), a non-linear optimization method.

https://jonathan-hui.medium.com/rl-lqr-ilqr-linear-quadratic-regulator-a5de5104c750.



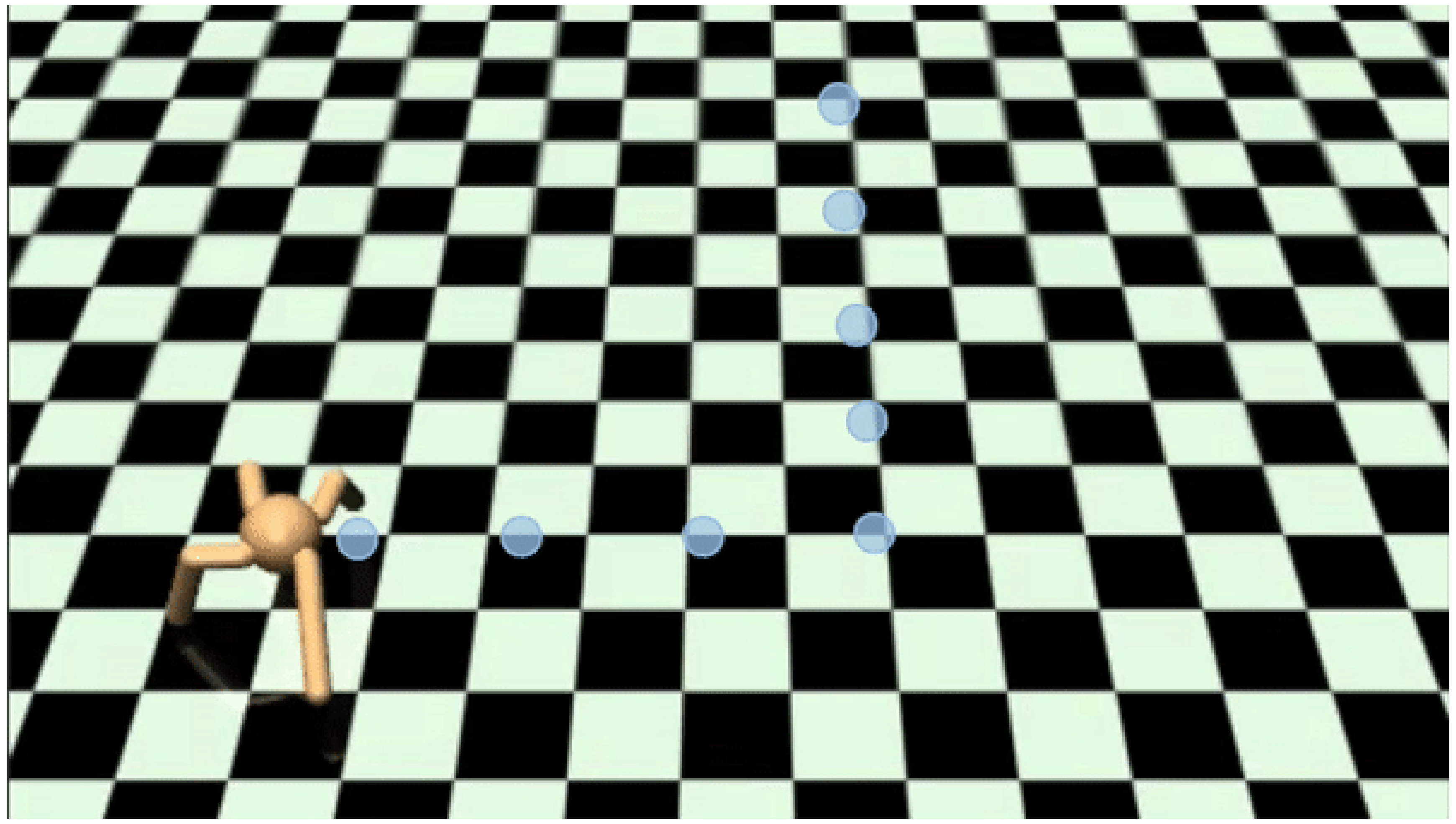
Source: https://bair.berkeley.edu/blog/2017/11/30/model-based-rl/

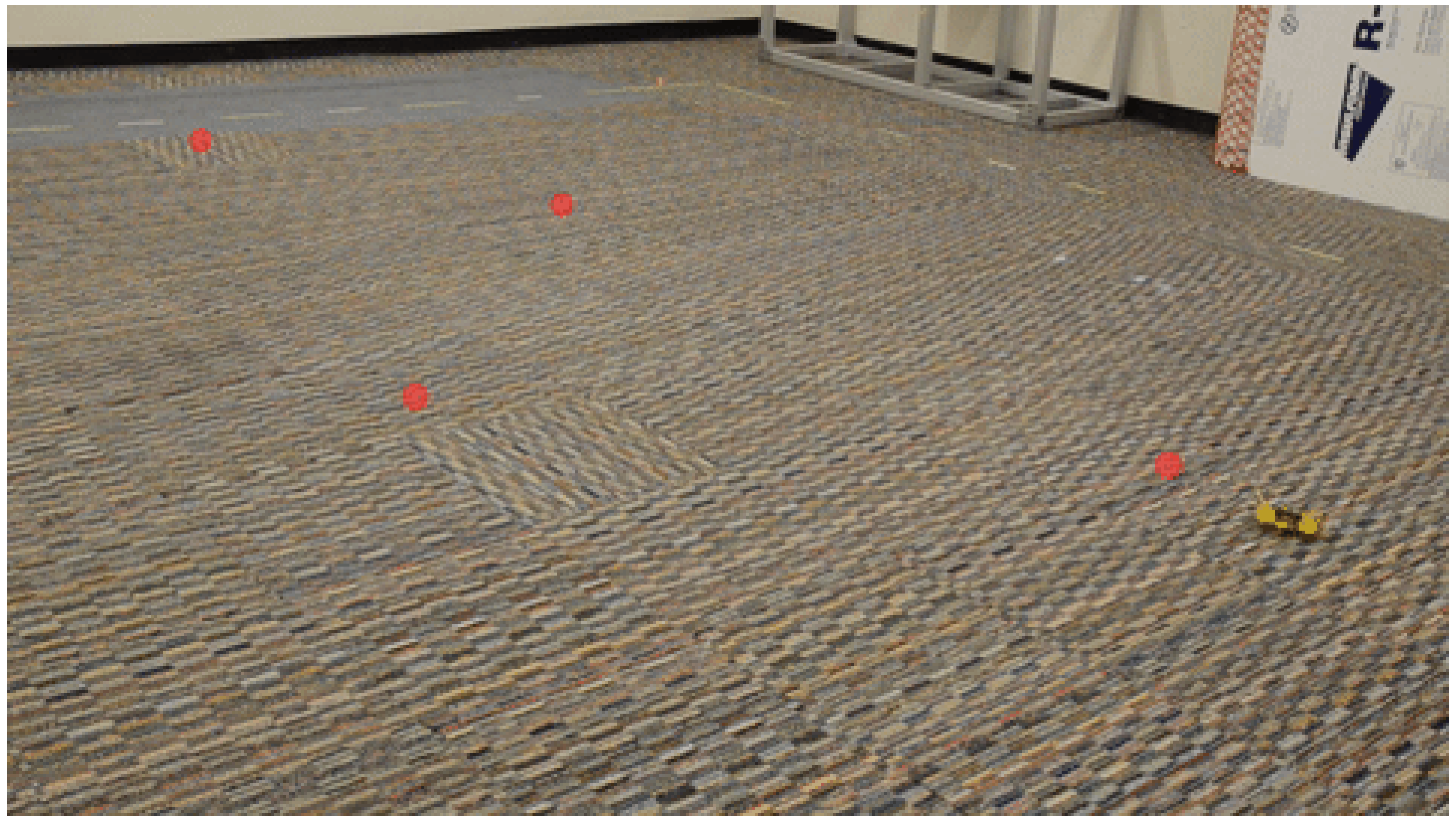
- **Random-sampling shooting**:
    1. in the current state, select a set of possible actions.
    2. generate rollouts with these actions and compute their returns using the model.
    3. select the action whose rollout has the highest return.
- Stochastic sampling methods such as the **cross-entropy method** CEM, where the policy is sampled using Bayesian methods (Szita and Lörincz, 2006),
- Genetic algorithms such as **Evolutionary Search** (ES) (Salimans et al., 2017)…

Nagabandi et al. (2017) Neural Network Dynamics for Model-Based Deep Reinforcement Learning with Model-Free Fine-Tuning. arXiv:1708.02596.

MPC - Example with a neural model

- The main advantage of MPC is that you can change the reward function (the **goal**) on the fly: what you learn is the model, but planning is just an optimization procedure.
- You can set intermediary goals to the agent very flexibly: no need for a well-defined reward function.
- Model imperfection is not a problem as you replan all the time. The model can adapt to changes in the environment (slippery terrain, simulation to real-world).





Source: https://bair.berkeley.edu/blog/2017/11/30/model-based-rl/

2 - World models

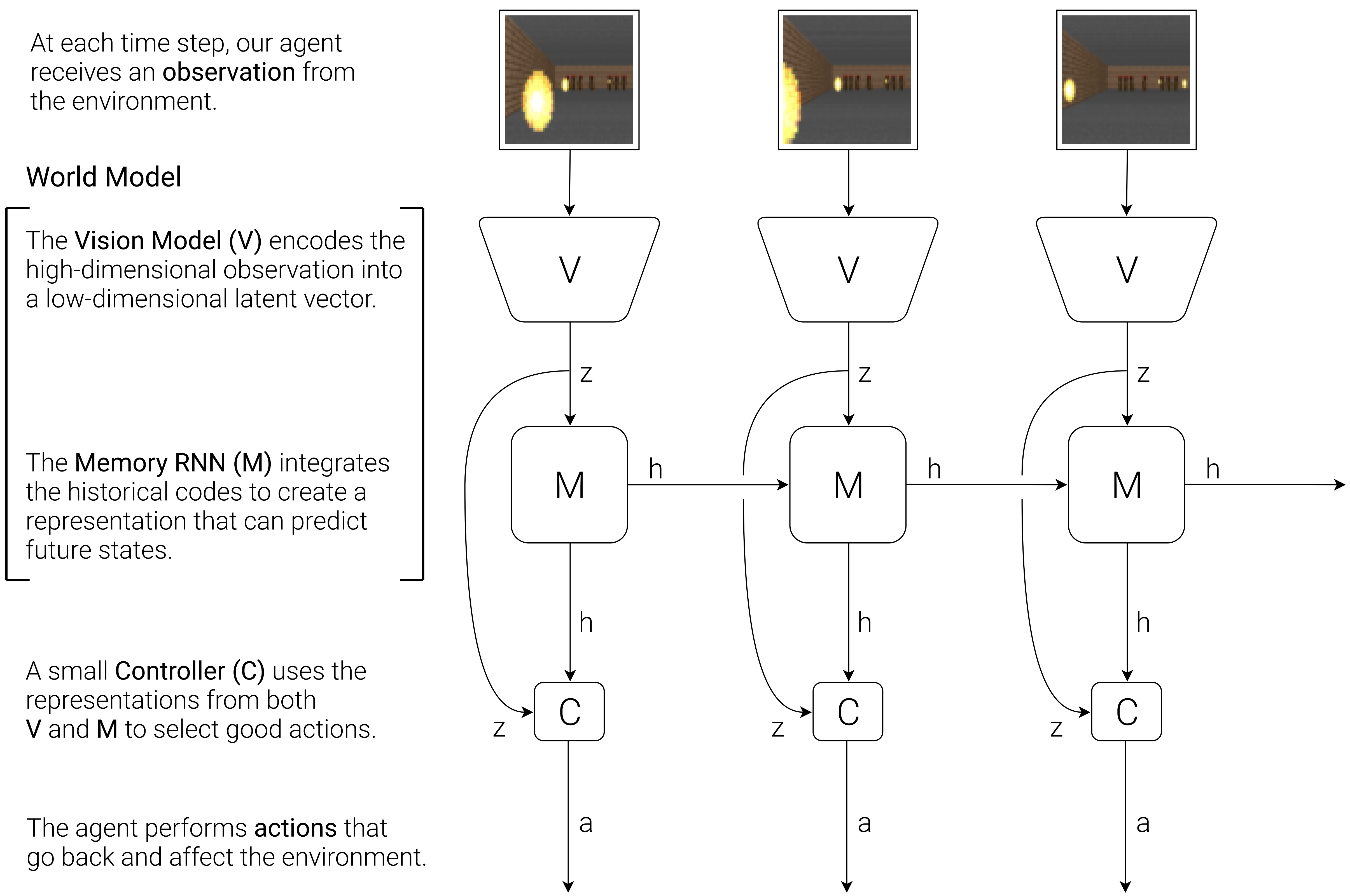
World Models

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

https://worldmodels.github.io/

World models

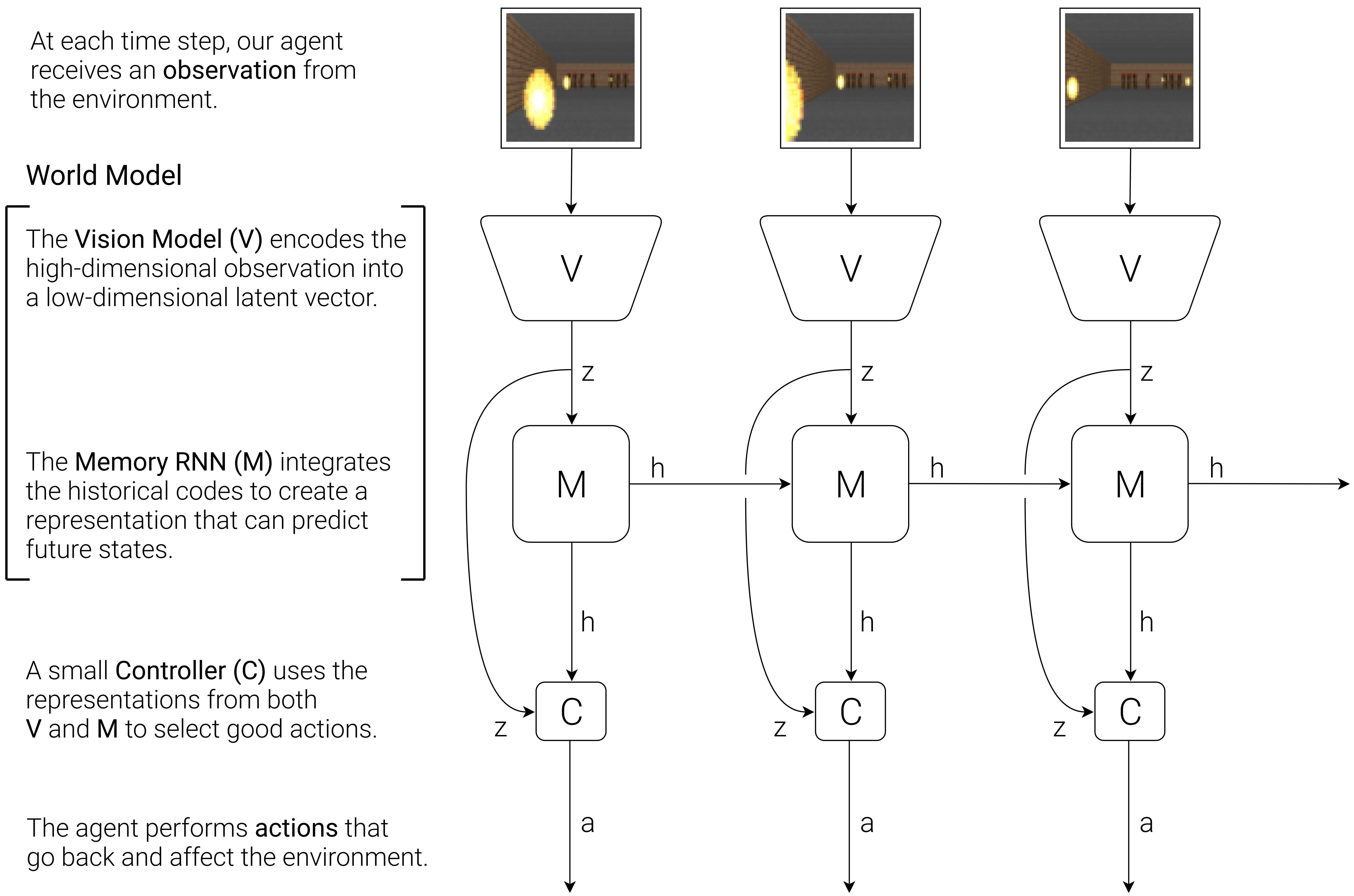
- The core idea of **world models** is to explicitly separate the **world model** (what will happen next) from the **controller** (how to act).
- Deep RL NN are usually small, as rewards do not contain enough information to train huge networks.



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/

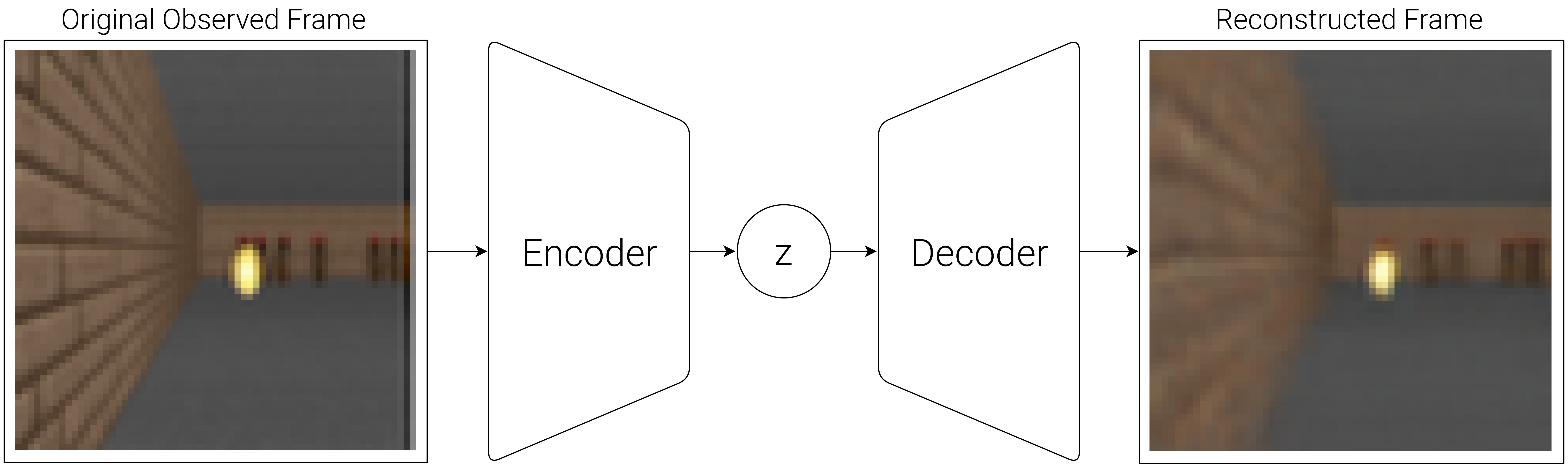
The Vizdoom Take Cover environment

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

X

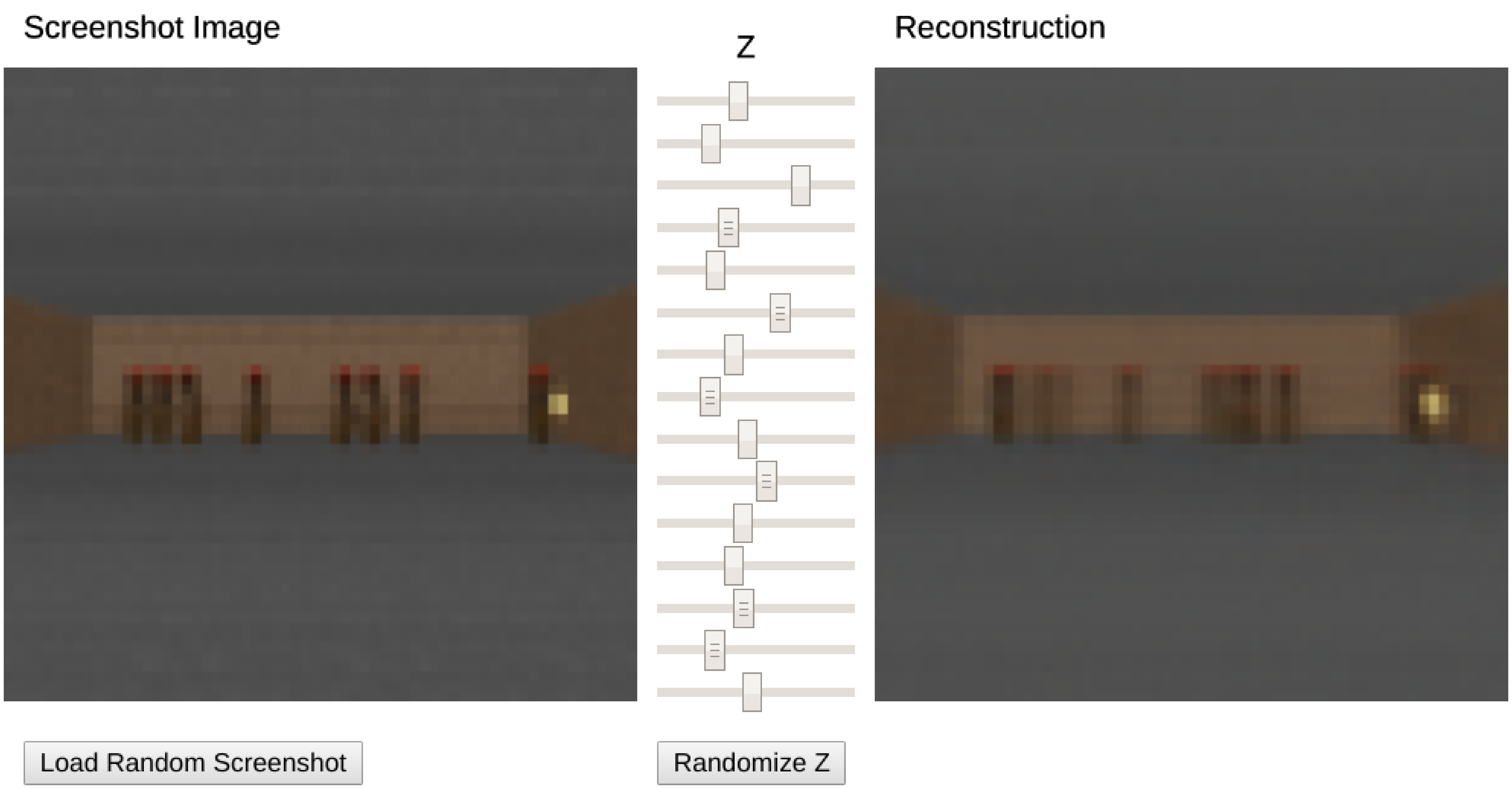
World models

- 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/

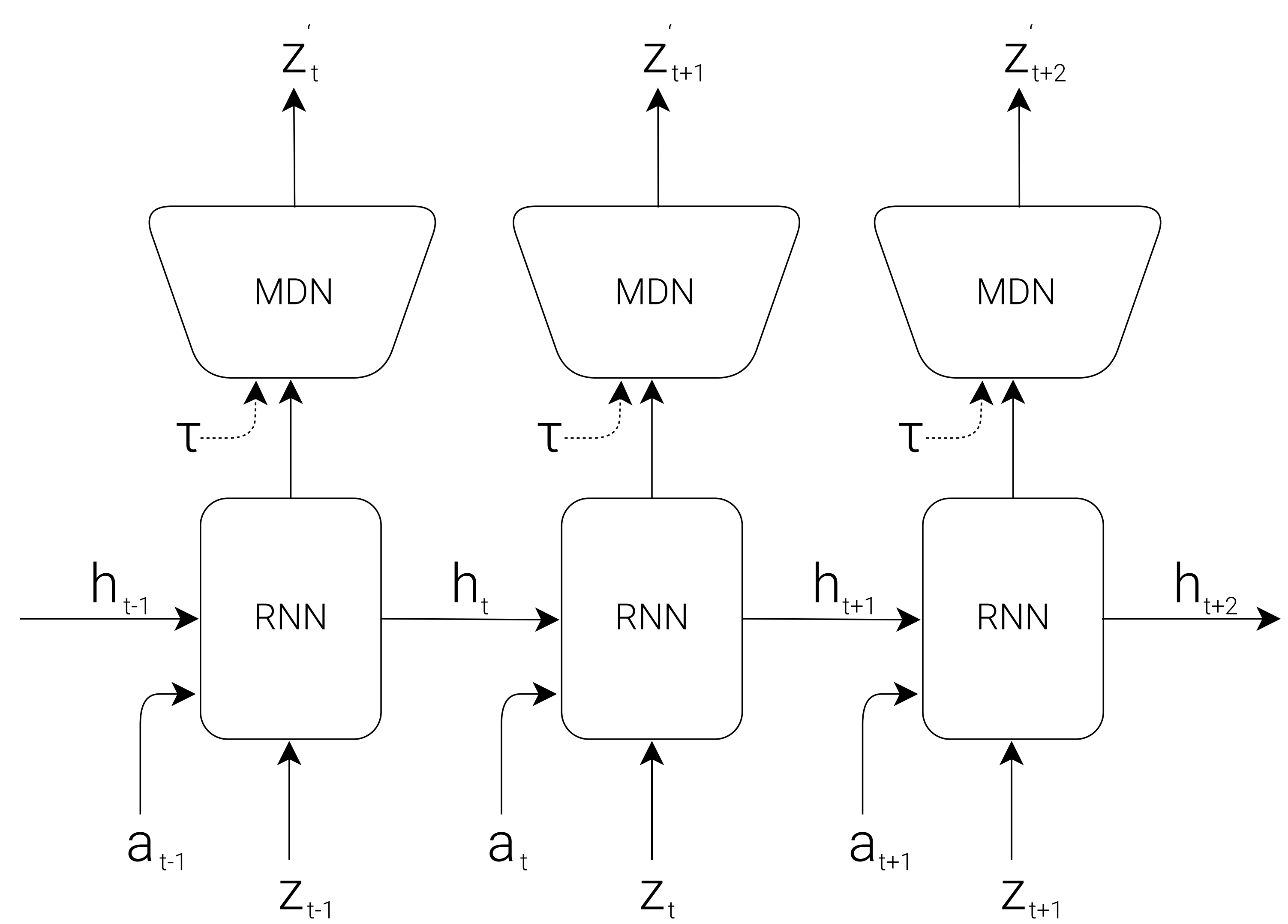
World models



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

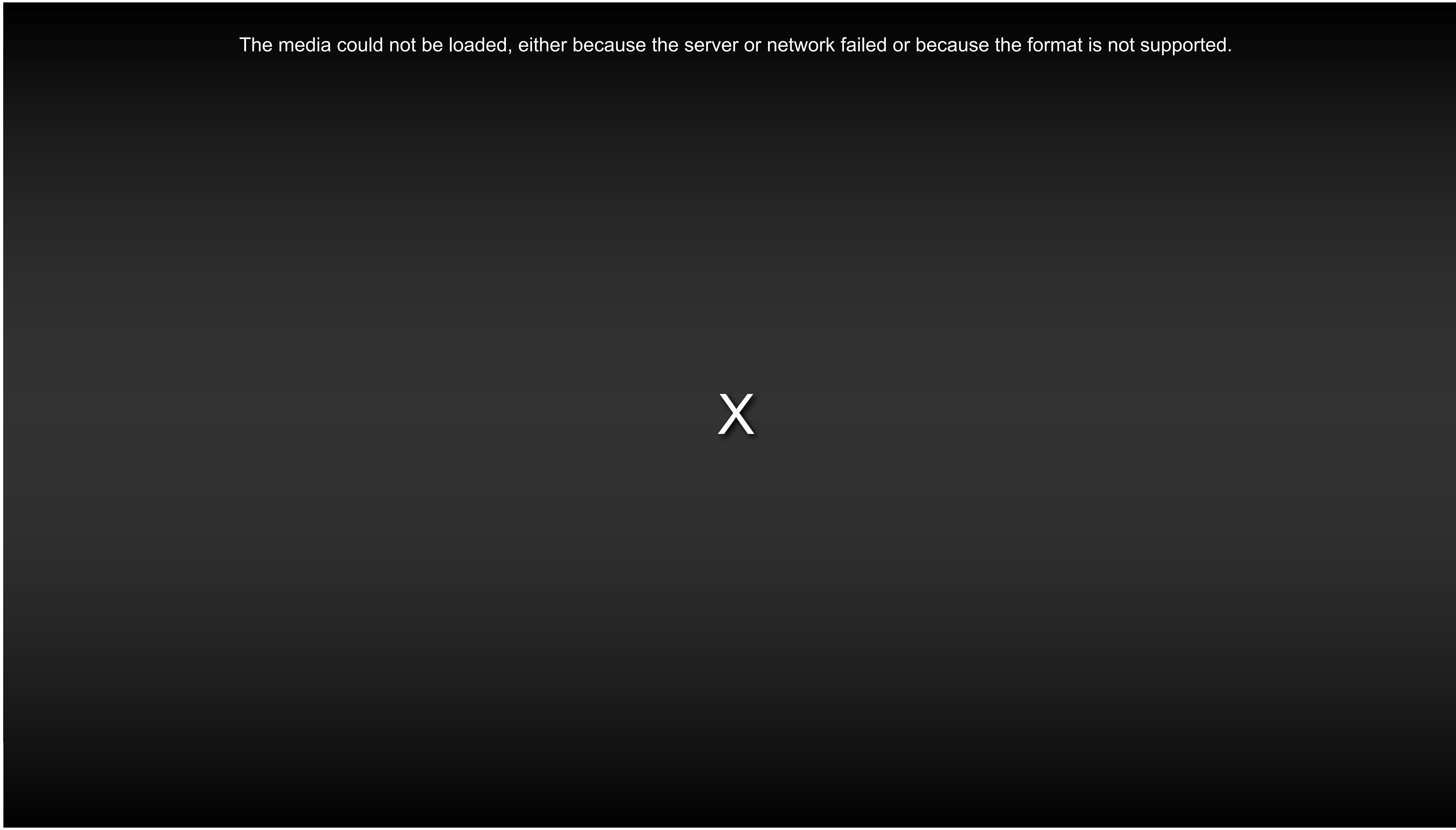
World models

- 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



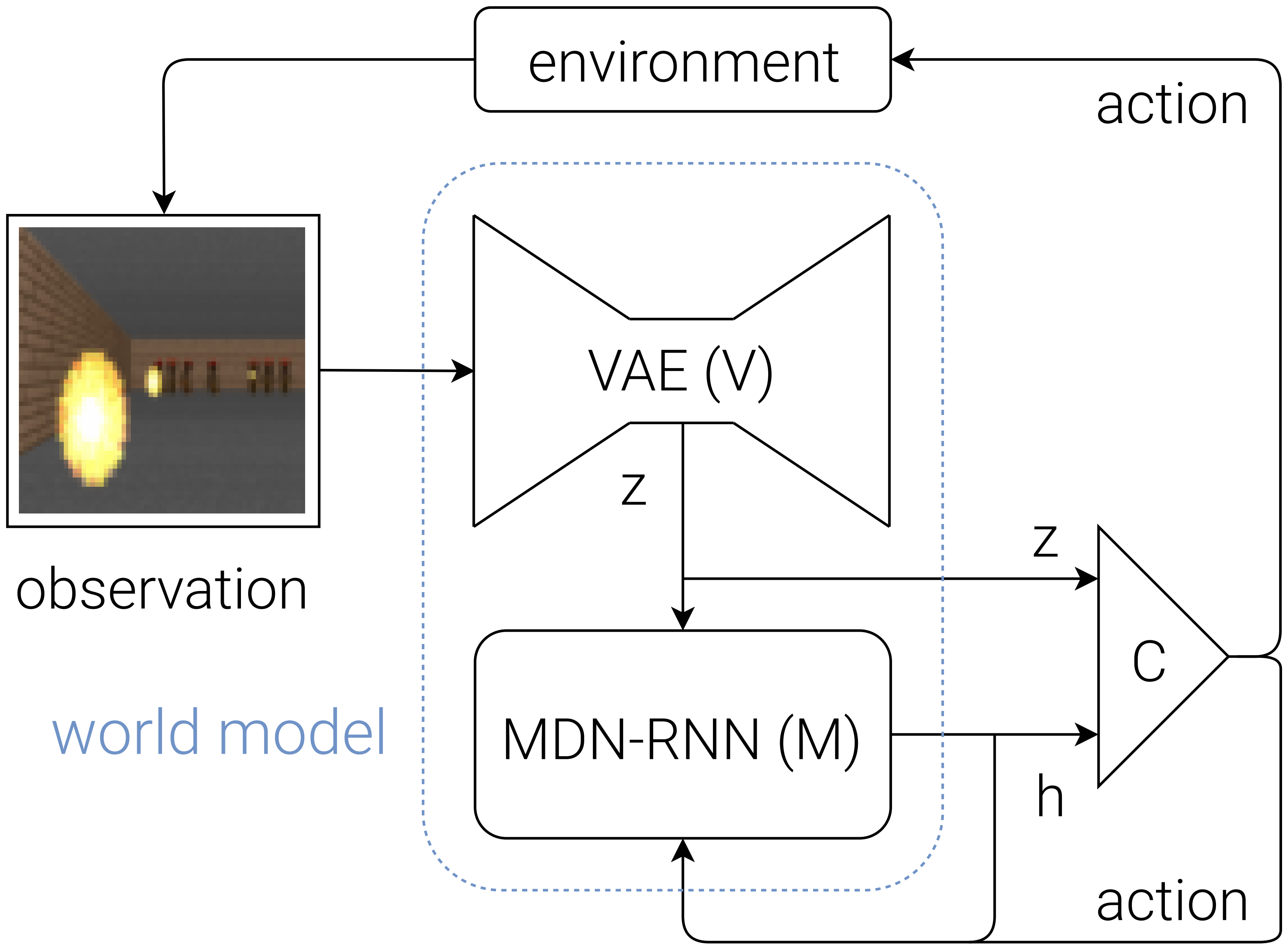
https://magenta.tensorflow.org/sketch-rnn-demo

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**:

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

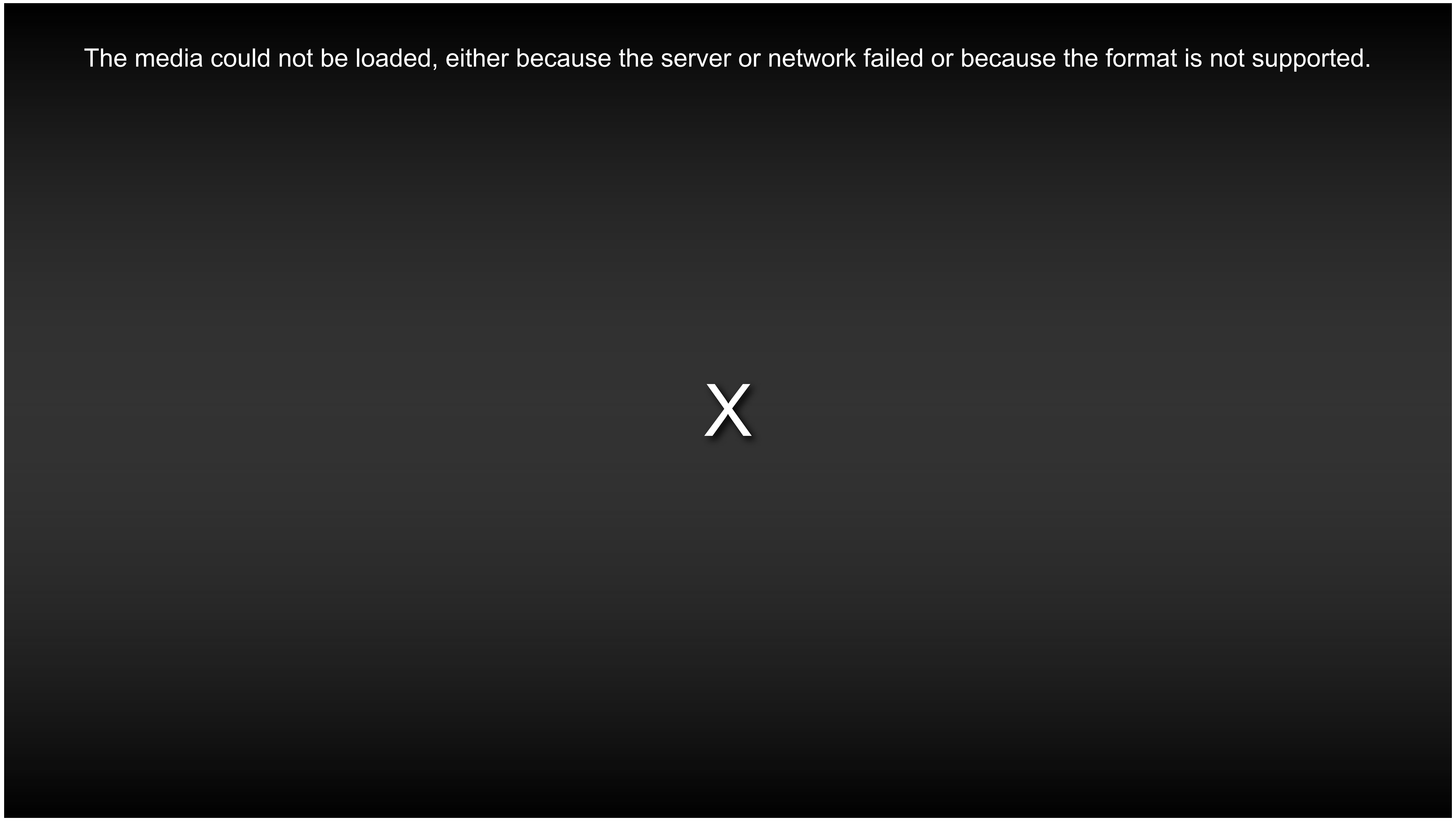
- A RL actor cannot get simpler as that...



https://worldmodels.github.io/

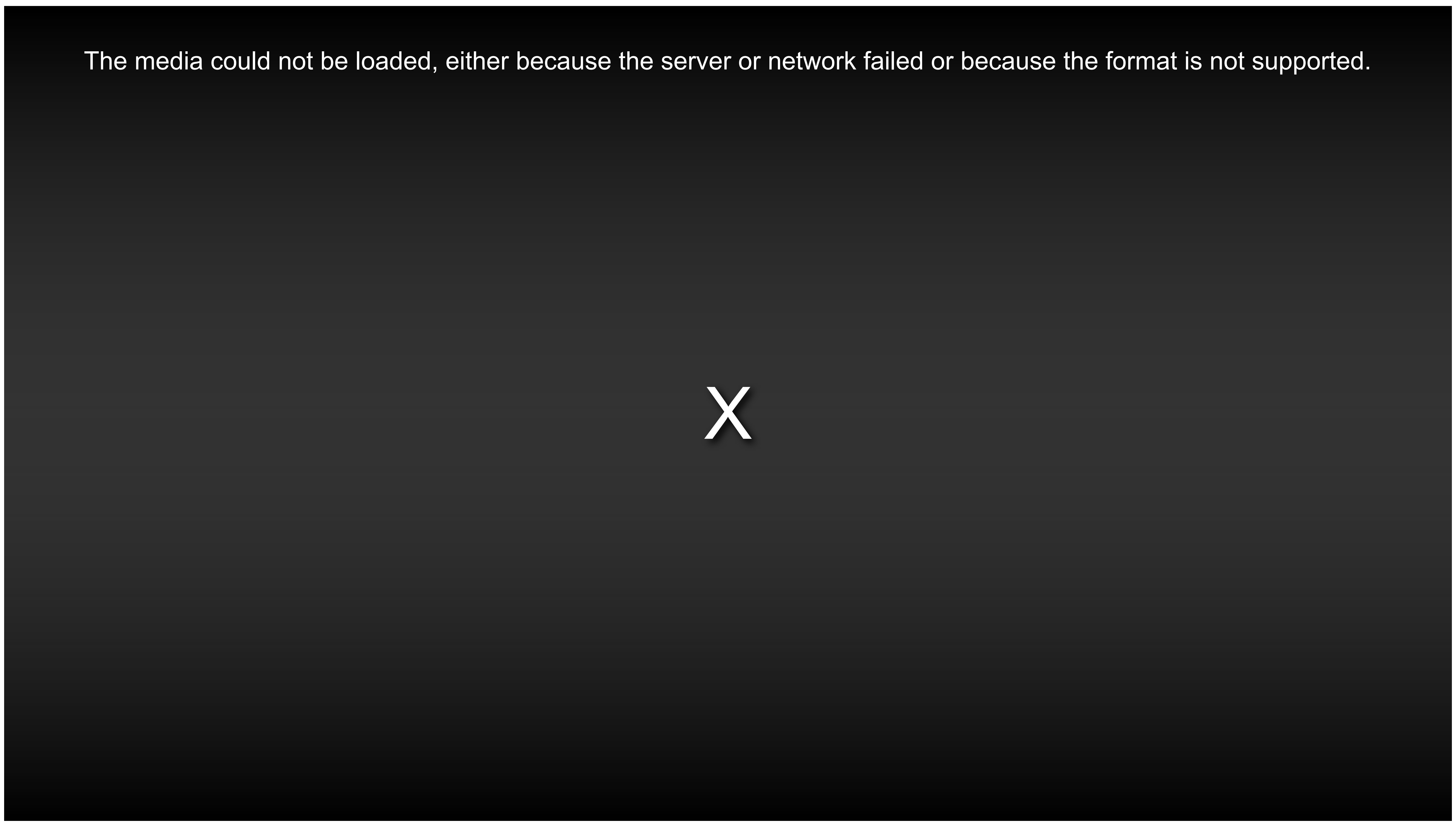
- The controller is not even trained with RL: it uses a genetic algorithm, the Covariance-Matrix Adaptation Evolution Strategy (CMA-ES), to find the output weights that maximize the returns.
- The world model is trained by classical supervised learning using a random agent before learning.

World models : car racing



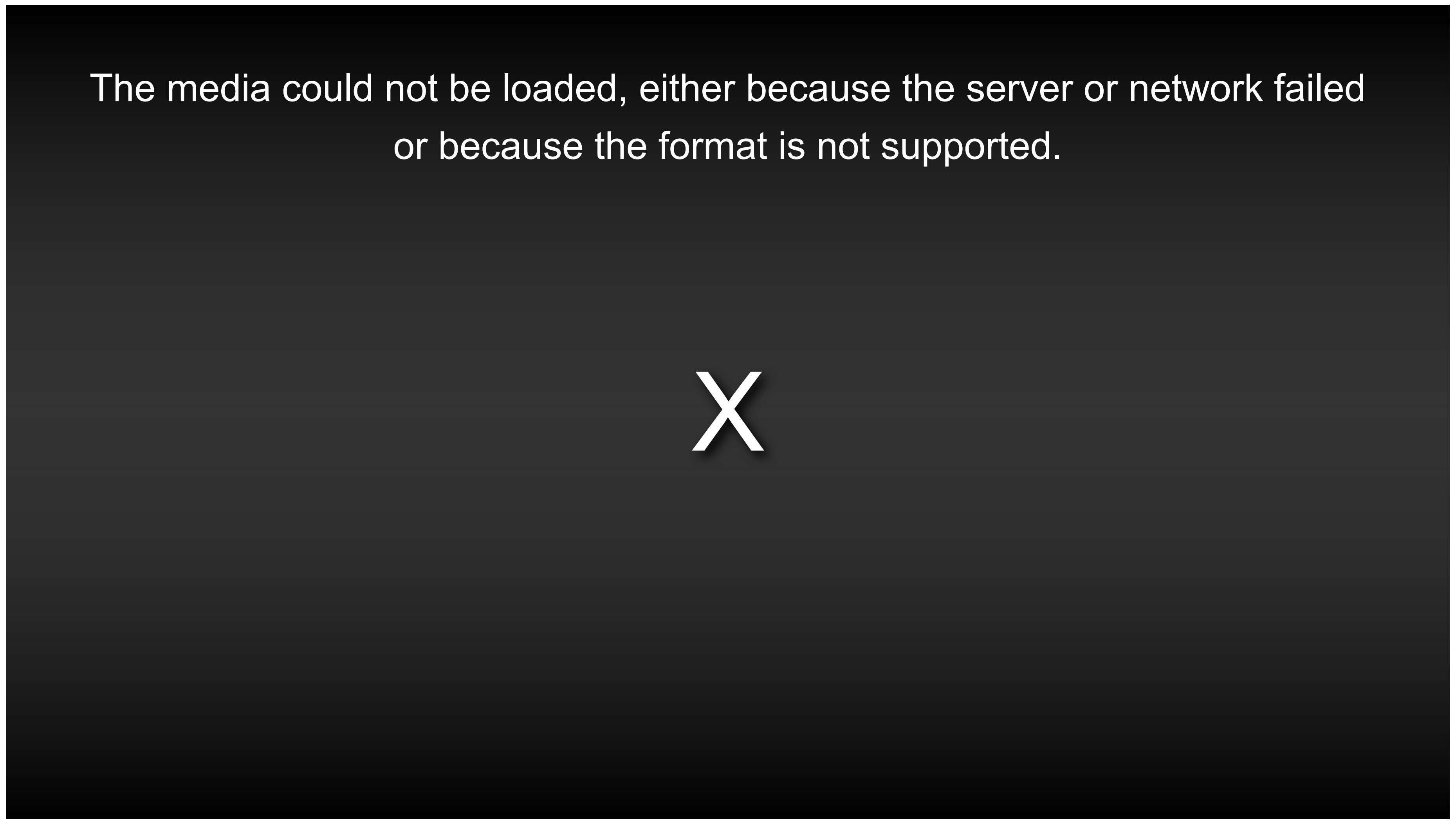
World models : car racing

- 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.

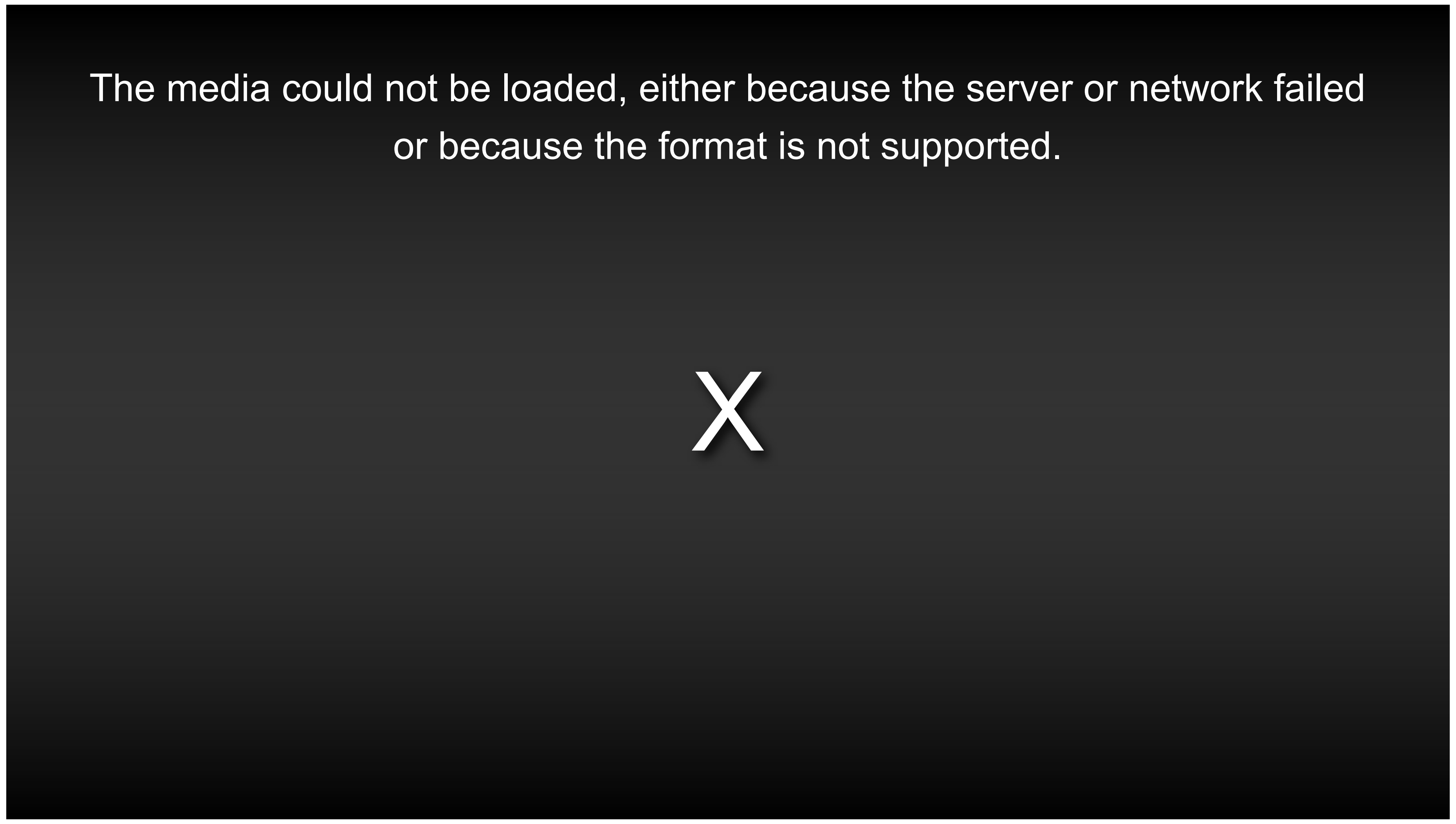


World models : car racing

- 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 $P(\mathbf{z}_{t+1} | a_t, \mathbf{h}_t, \dots \mathbf{z}_t)$.
4. Evolve Controller (C) to maximize the expected cumulative reward of a rollout.

Parameters for car racing:

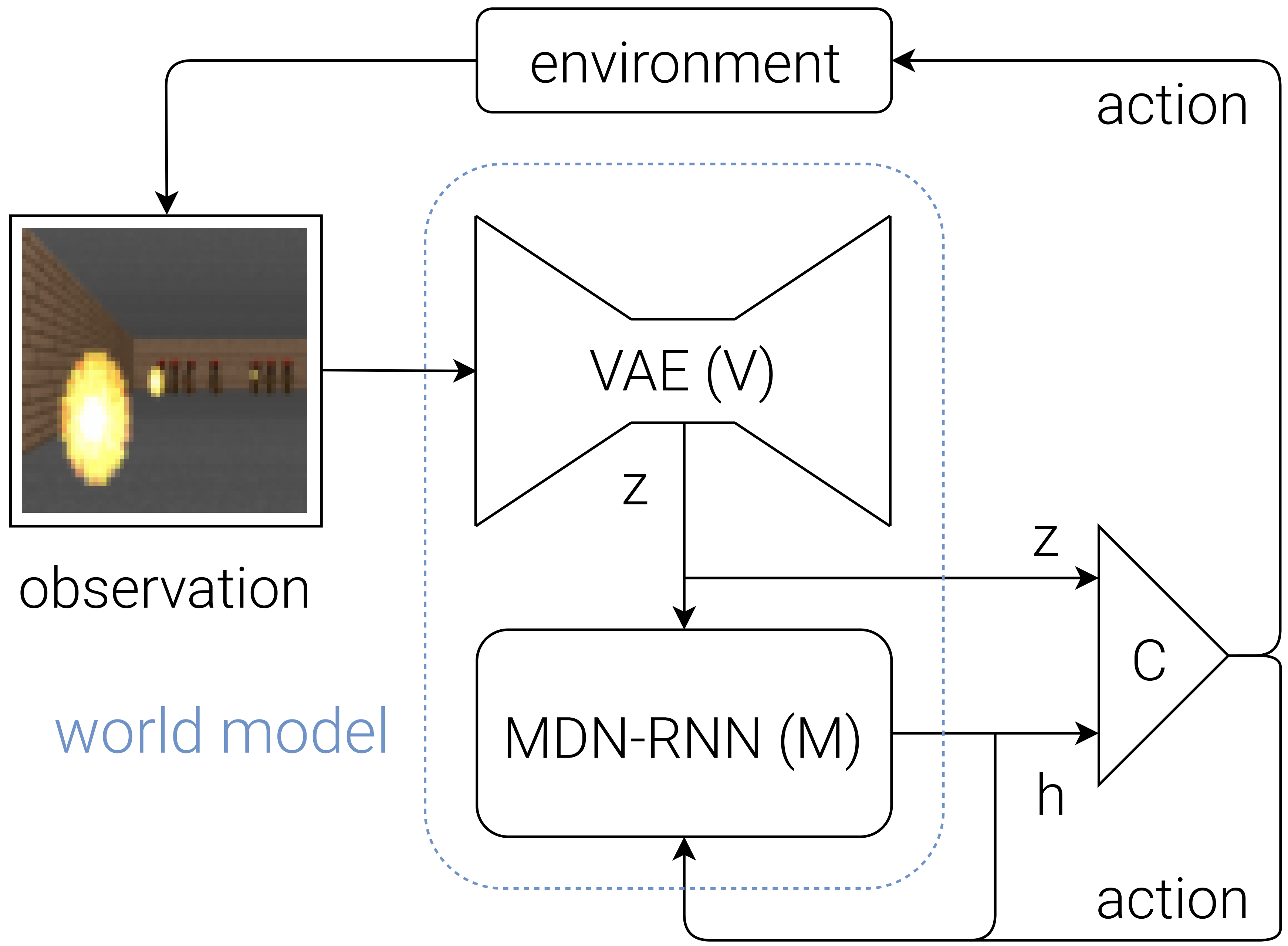
Model	Parameter Count
VAE	4,348,547
MDN-RNN	422,368
Controller	867

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.

3 - 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]

Hafner et al. (2019) Learning Latent Dynamics for Planning from Pixels. arXiv:181104551

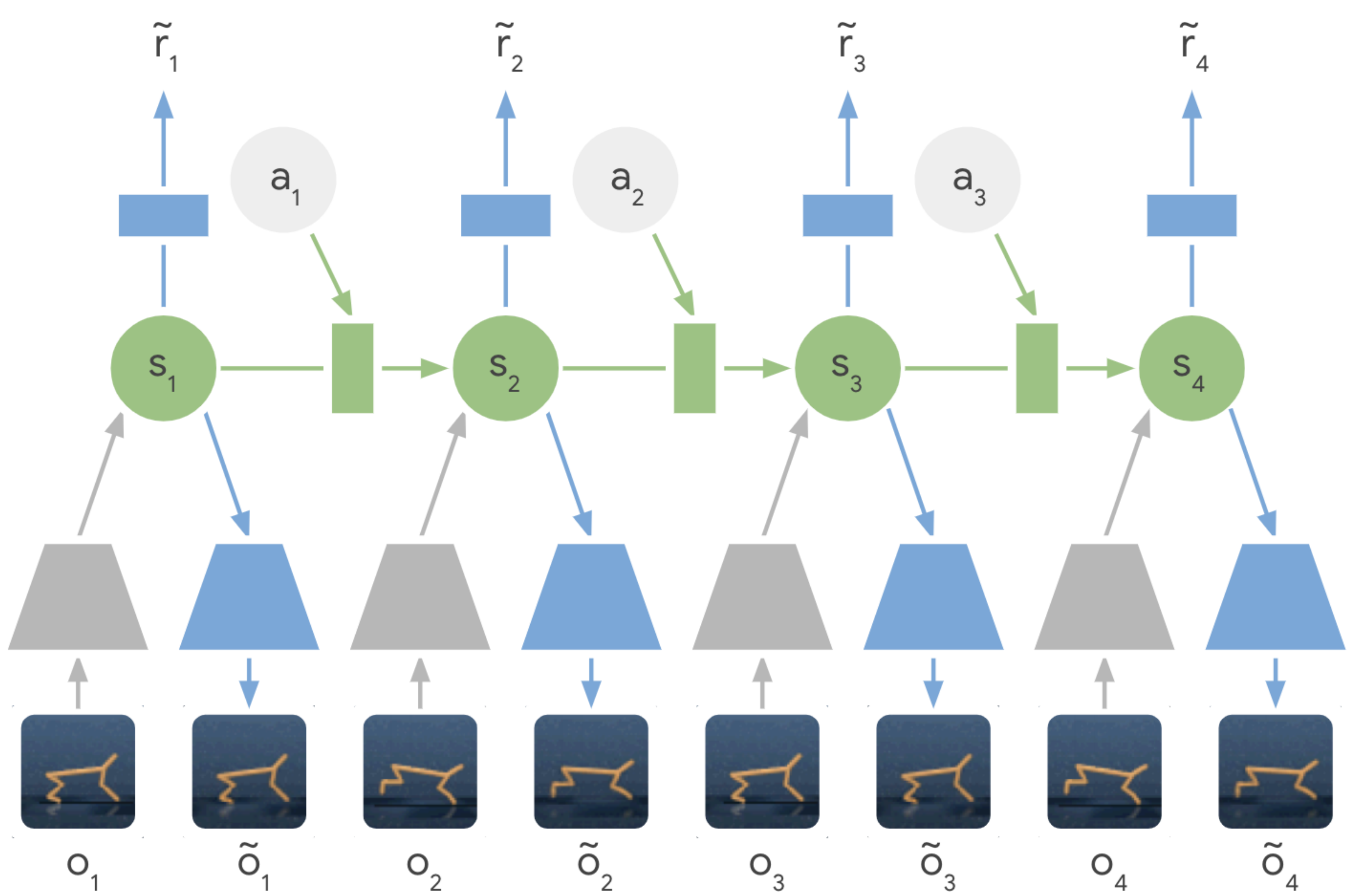
PlaNet

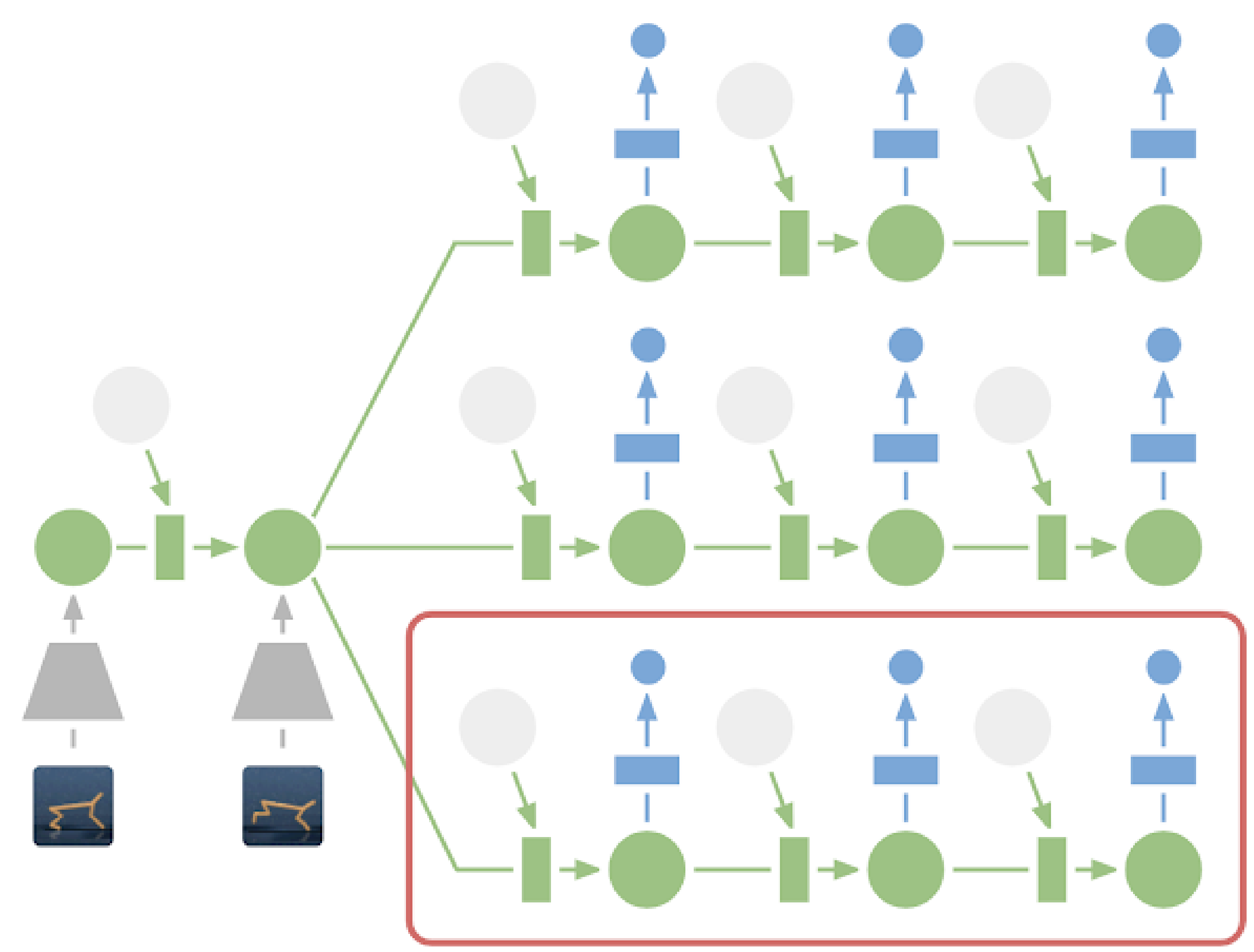
- PlaNet extends the idea of World models by learning the model together with the policy (**end-to-end**).
- It learns a **latent dynamics model** that takes the past observations o_t into account (needed for POMDPs):

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

and plans in the latent space using multiple rollouts:

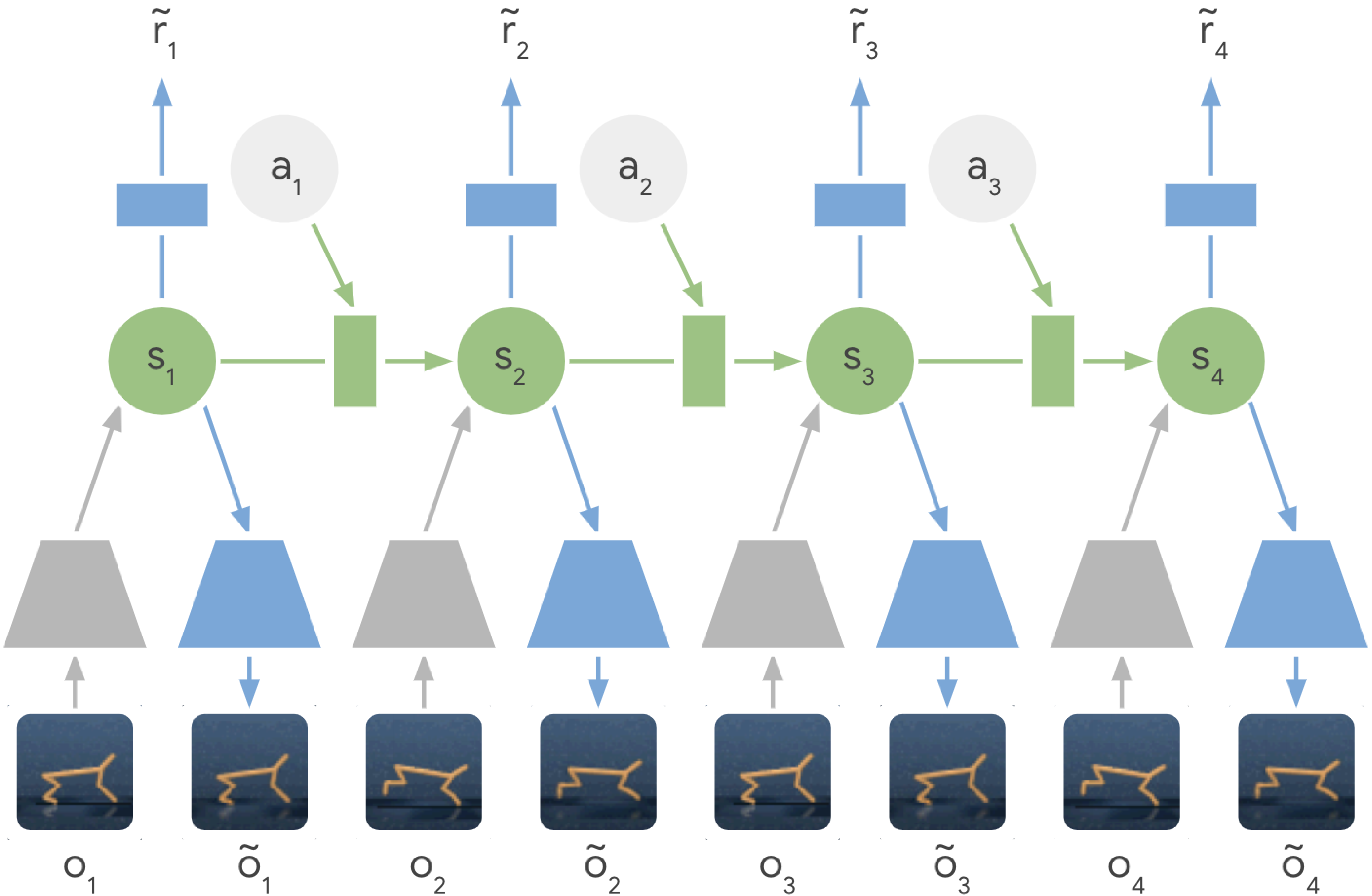
$$a_t = \arg\max_a \mathbb{E}[R(s_t, a, s_{t+1}, \ldots)]$$





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 $\hat{o}_t$.

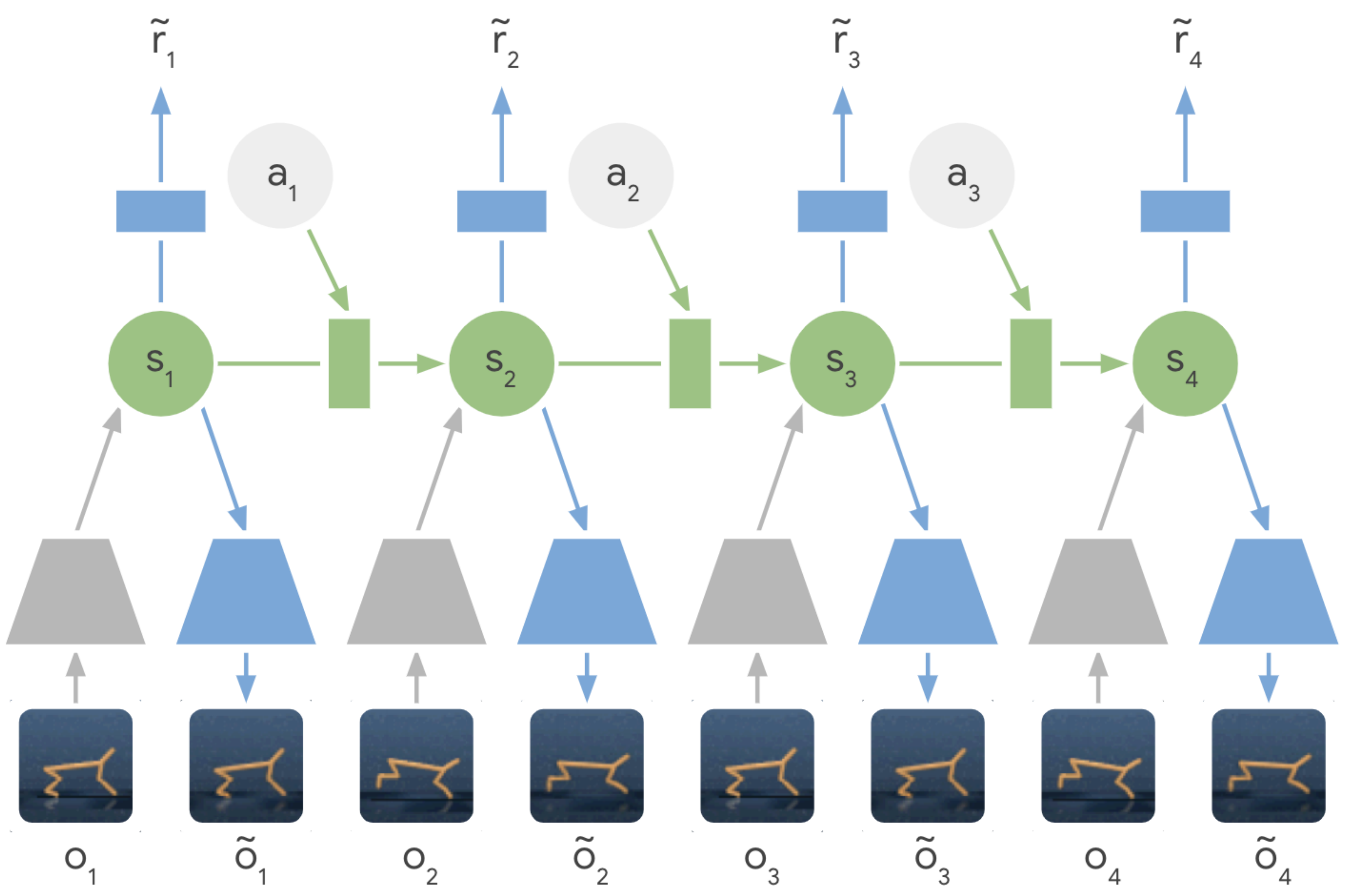
$$p(\hat{o}_t | s_t)$$

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.

$$p(r_t | s_t)$$



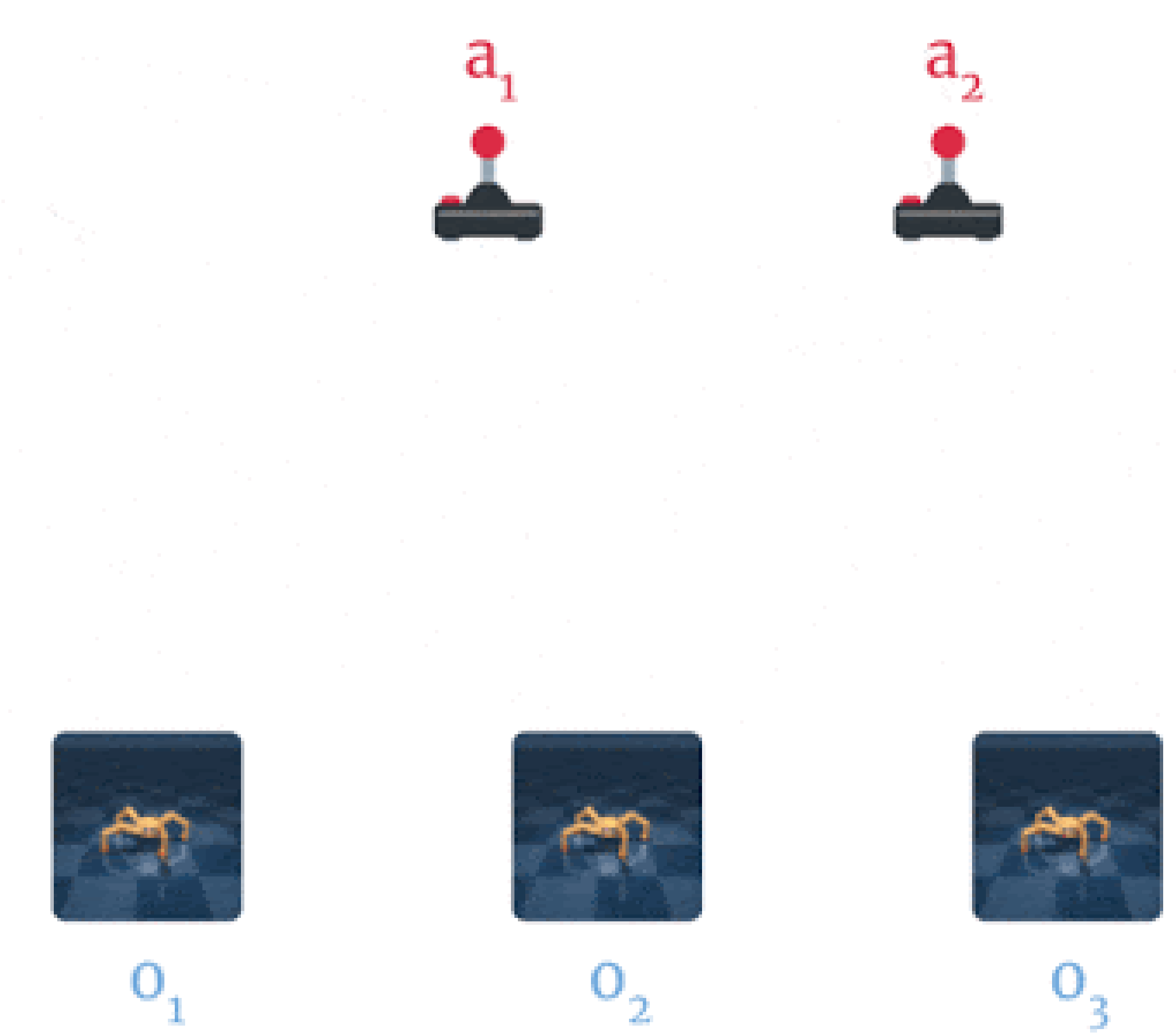
Source: https://ai.googleblog.com/2019/02/introducing-planet-deep-planning.html

PlaNet: latent dynamics model

- The loss function to train this **recurrent state-space model** (RSSM) simply adds up the three learning objectives (VAE + world model + reward).

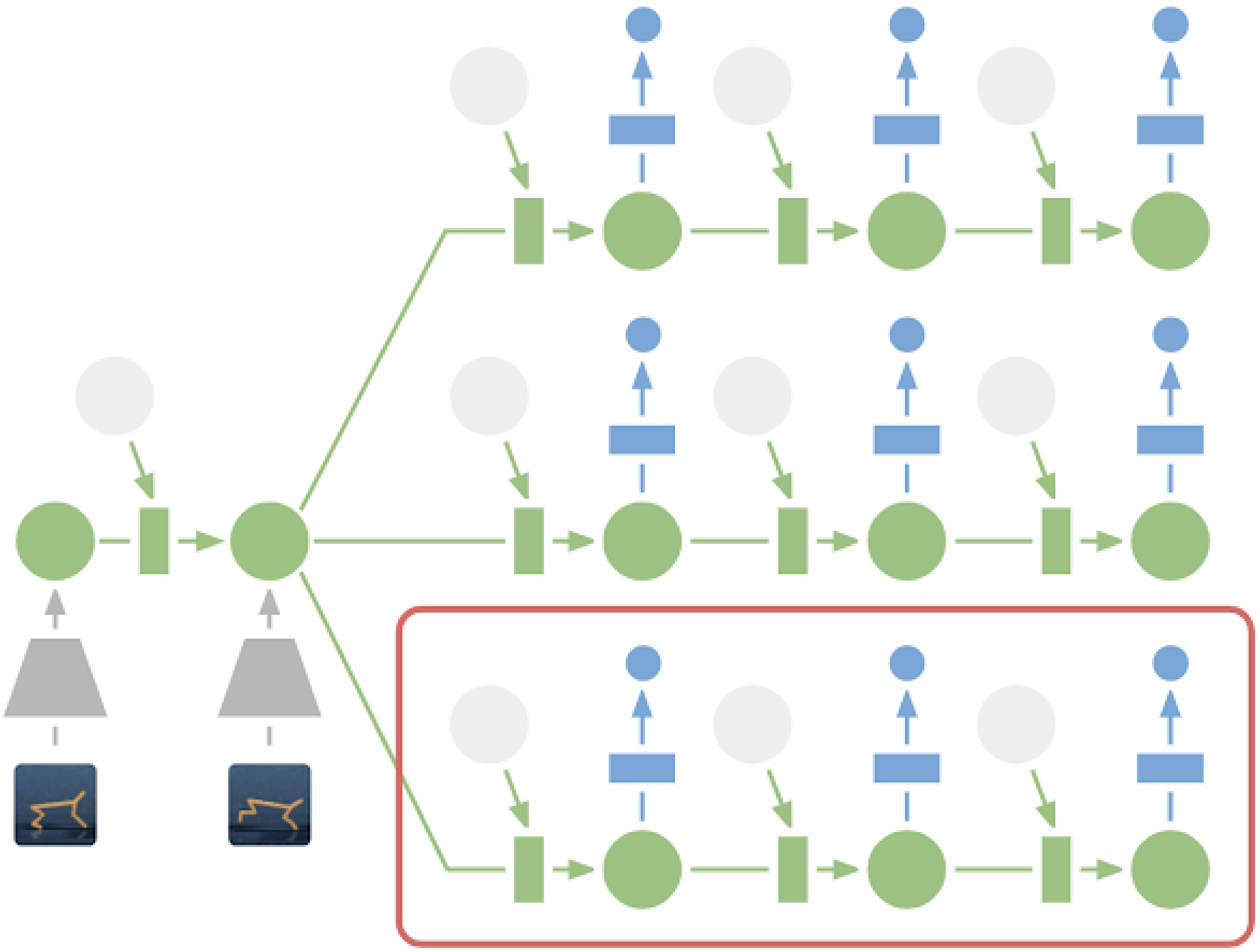
$$\mathcal{L}(\theta) = \mathcal{L}_\text{reconstruction}(\theta) + \mathcal{L}_\text{prediction}(\theta) + \mathcal{L}_\text{reward}(\theta)$$

- Training sequences $(o_1, a_1, o_2, \ldots, o_T)$ can be generated **off-policy** (e.g. from demonstrations) or on-policy.
- Backpropagation through time (BPTT) can be applied on complete (or partial) sequences.



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

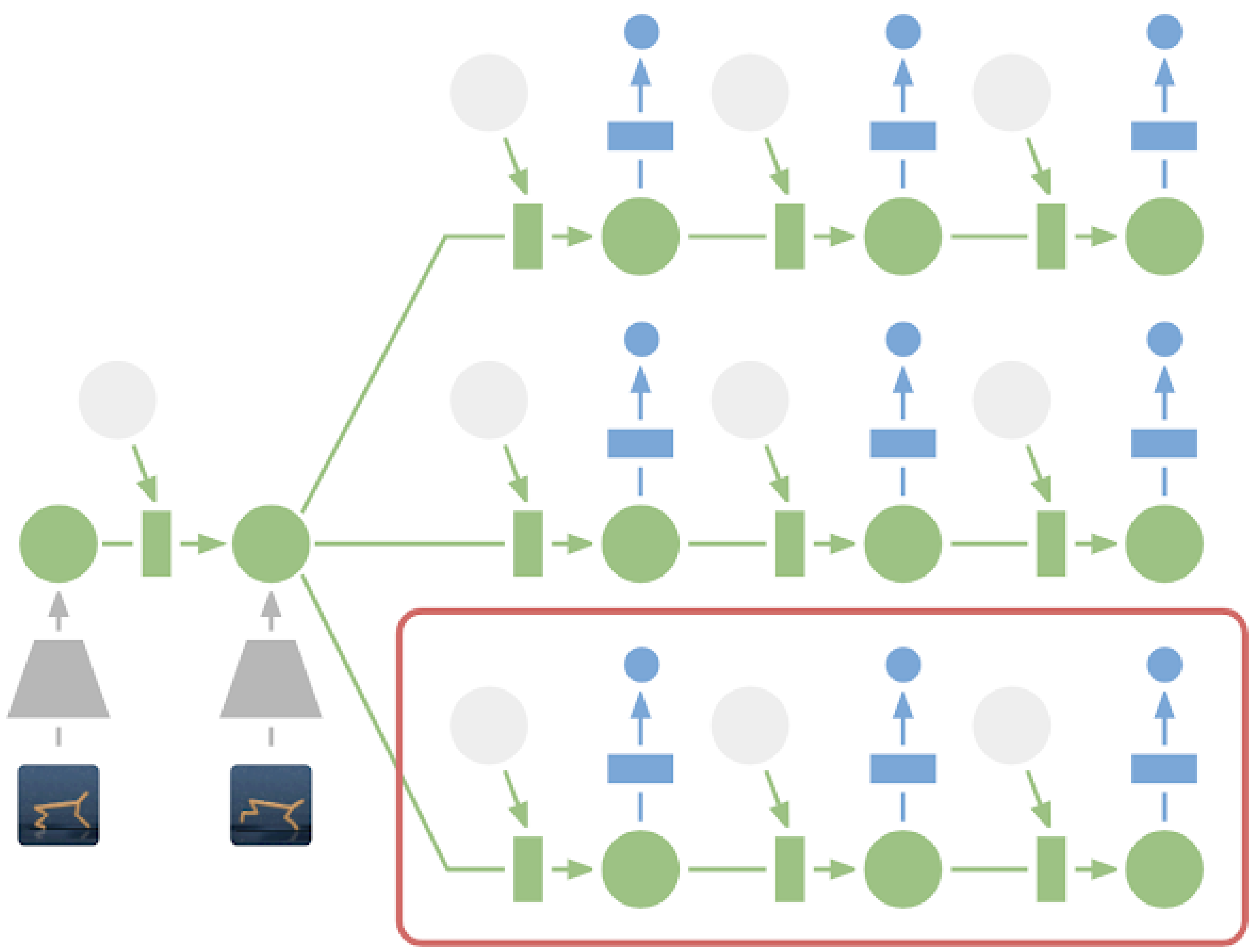
PlaNet: latent space planning



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

PlaNet: latent space planning

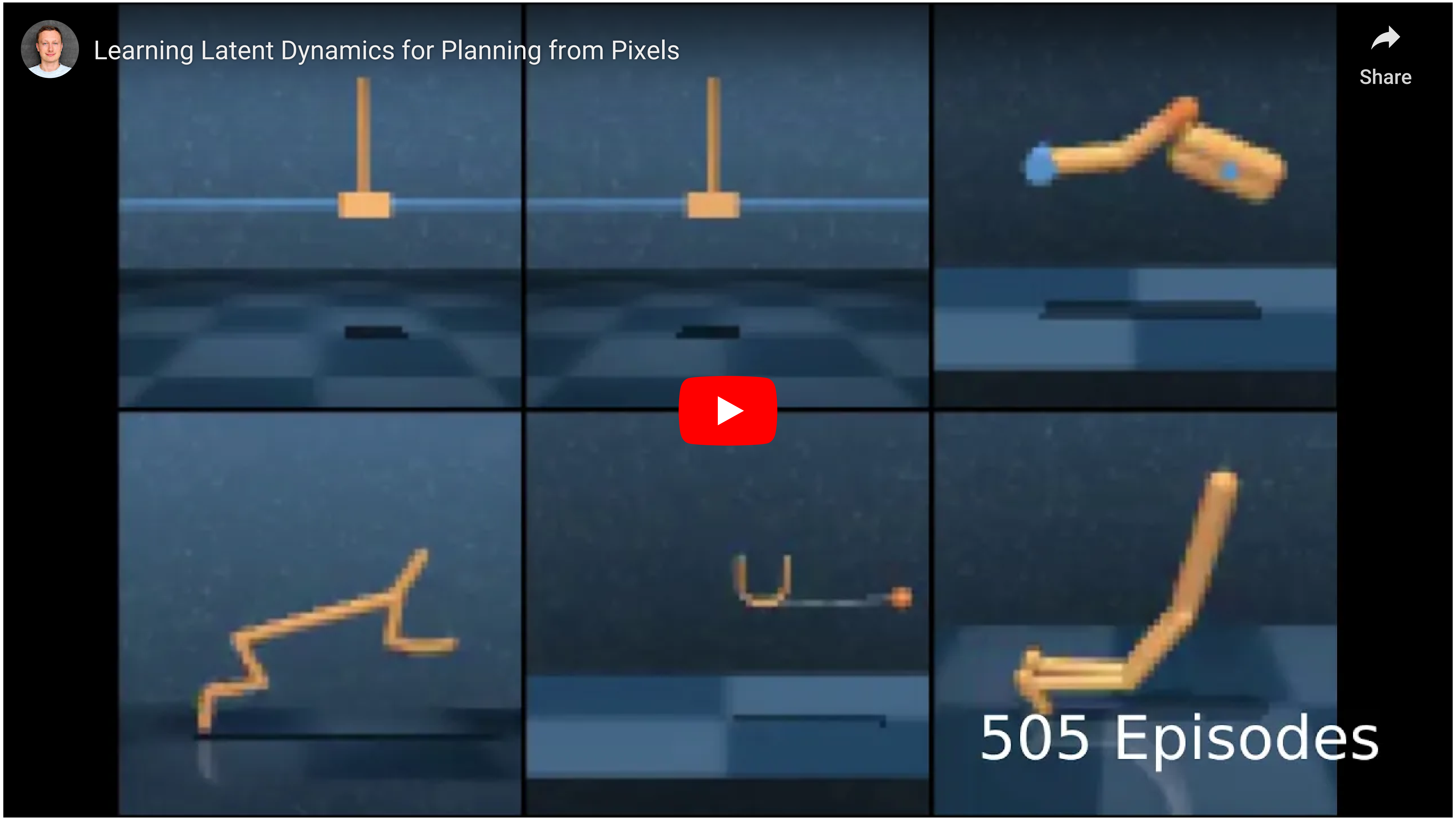
- From a single observation o_t encoded into s_t, 10000 rollouts are generated using **random sampling**.
- A belief over action sequences is updated using the **cross-entropy method** (CEM) in order to restrict the search.
- The first action of the sequence with the highest estimated return (reward 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

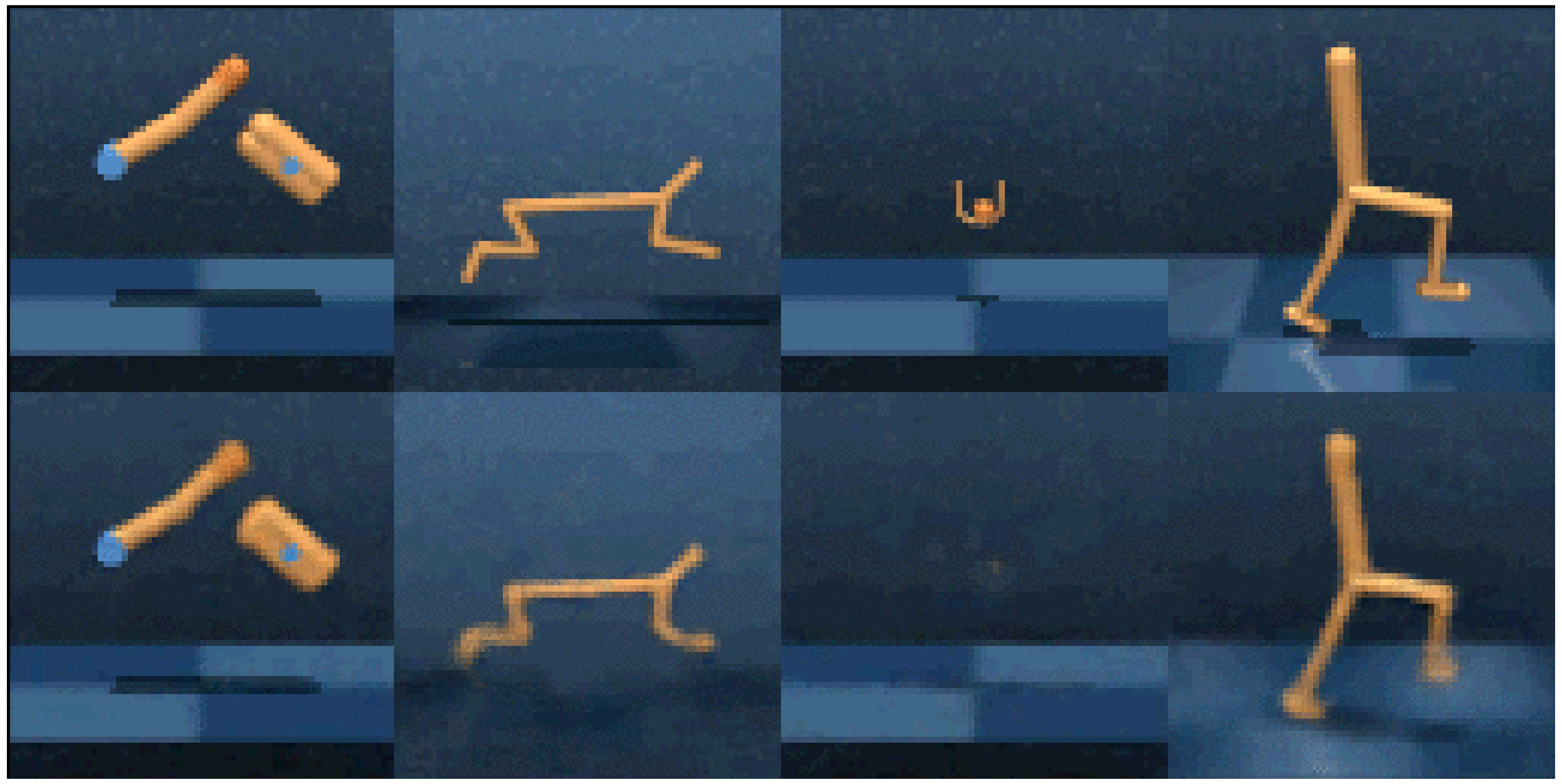
PlaNet results

- 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

4 - Dreamer

Published as a conference paper at ICLR 2020

DREAM TO CONTROL: LEARNING BEHAVIORS BY LATENT IMAGINATION

Danijar Hafner *
University of Toronto
Google Brain

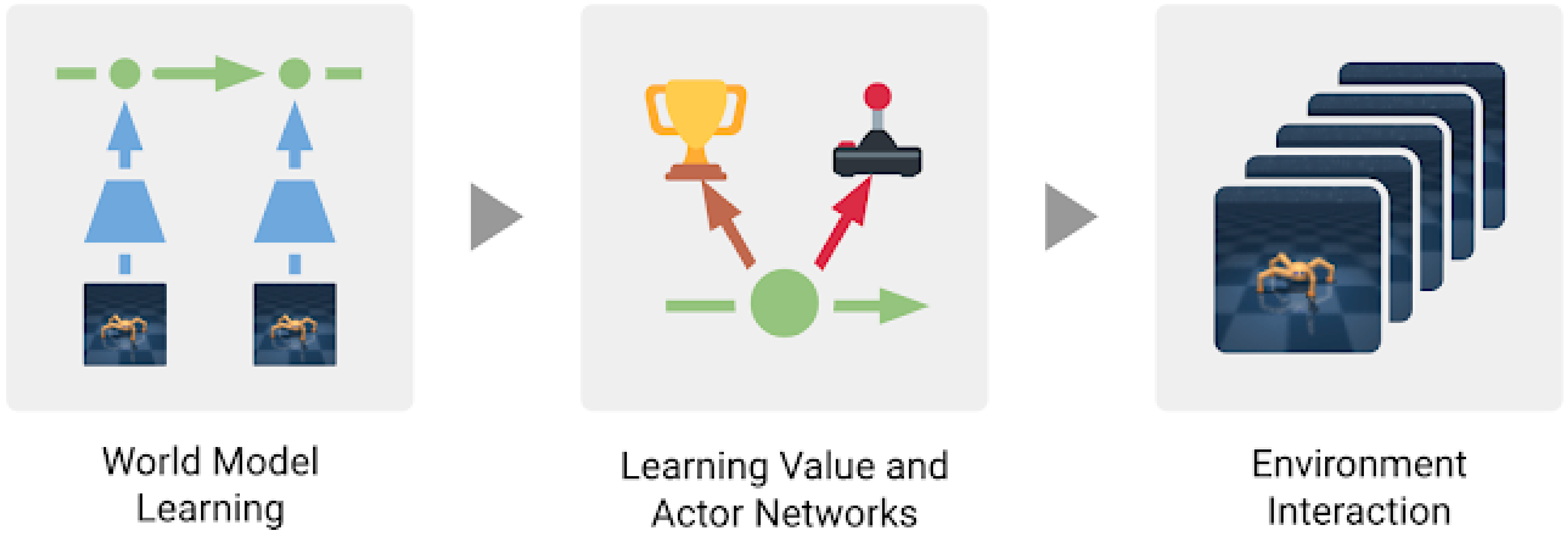
Timothy Lillicrap
DeepMind

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.

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:

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

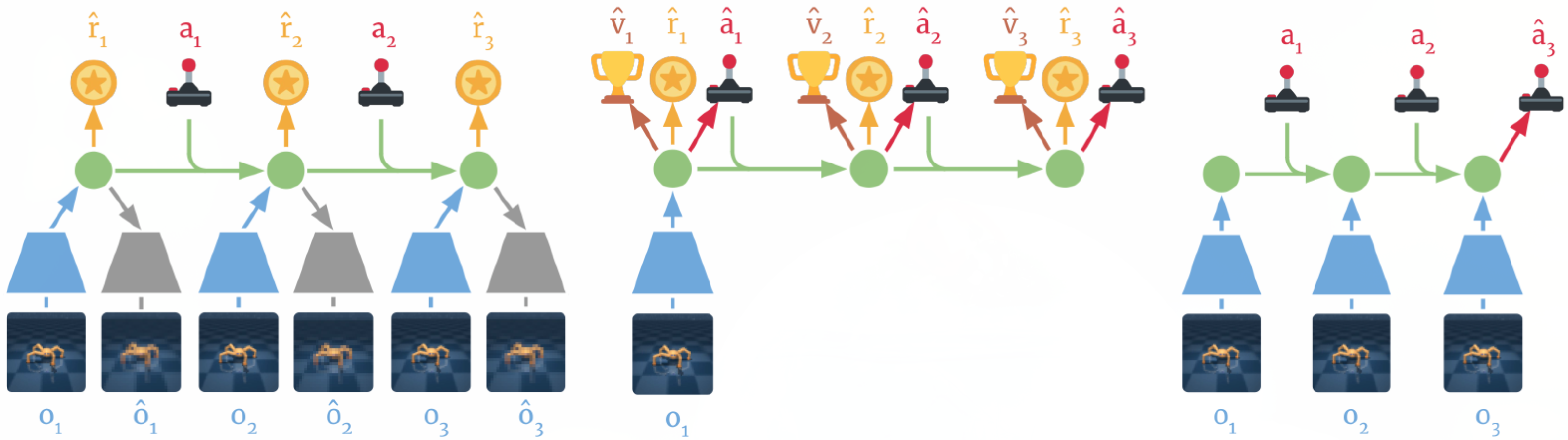
- The **actor** $\pi_\theta(s_t, a_t)$ is trained on the sequence to maximize the sum of the value of the future states:

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

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!

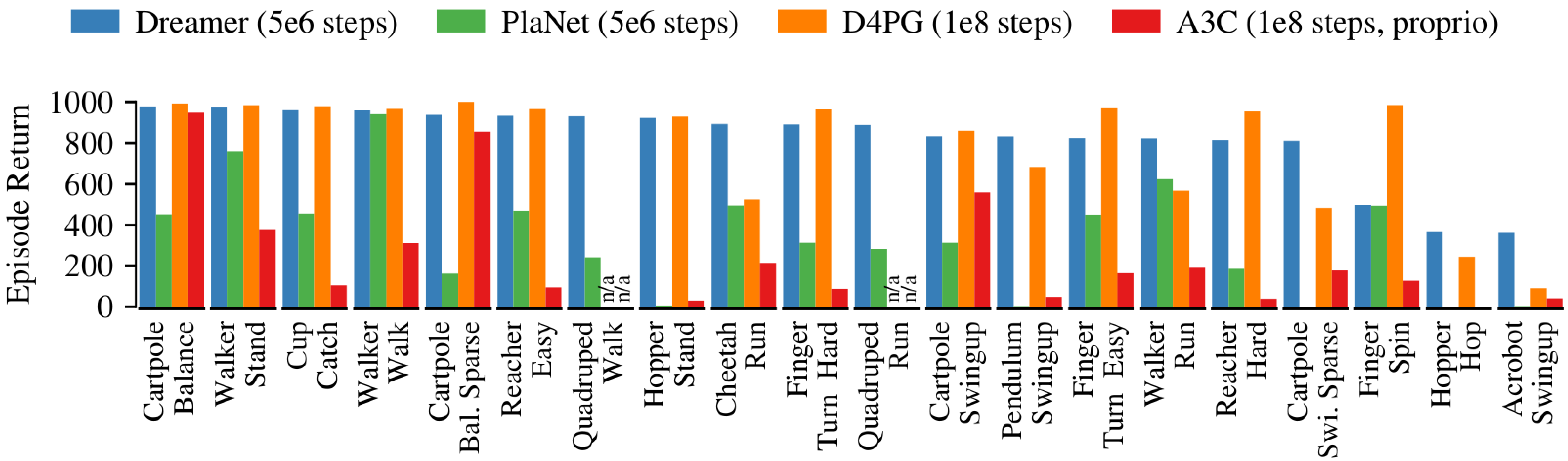


(a) Learn dynamics from experience (b) Learn behavior in imagination (c) Act in the environment

Hafner et al. (2020) Dream to Control: Learning Behaviors by Latent Imagination. arXiv:191201603

Dreamer results

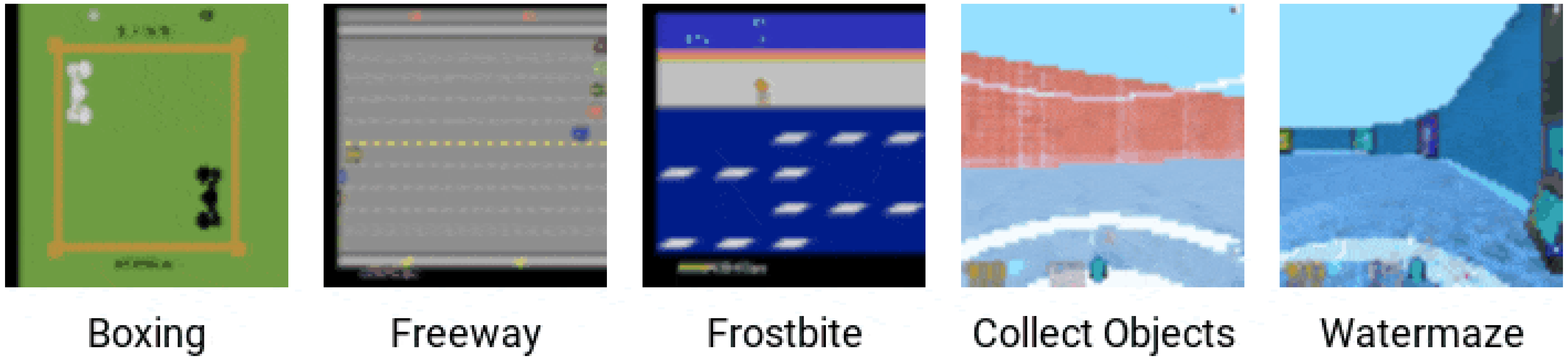
- Dreamer beats model-free and model-based methods on 20 continuous control tasks.

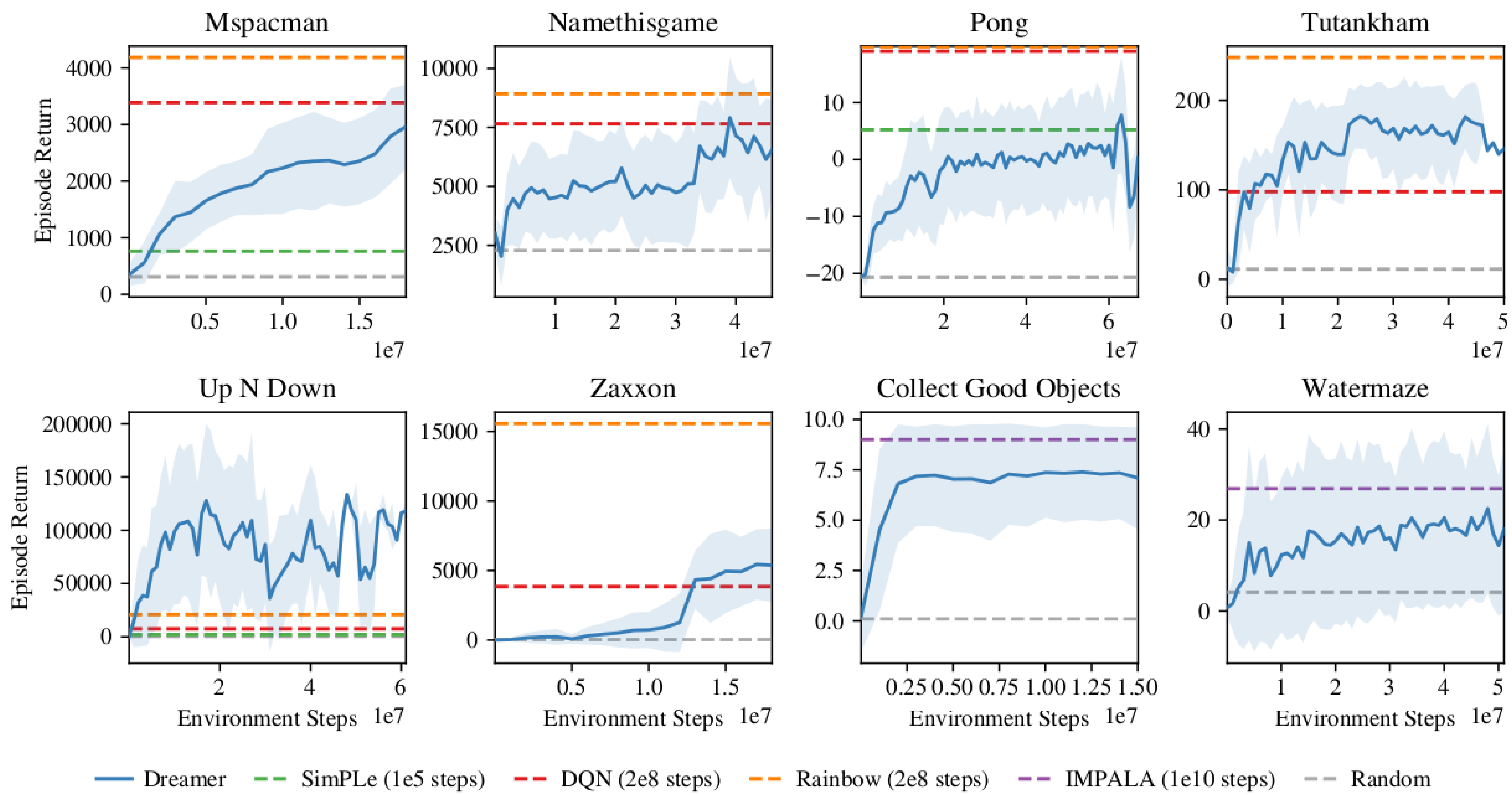


Source: https://ai.googleblog.com/2020/03/introducing-dreamer-scalable.html

Dreamer results

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



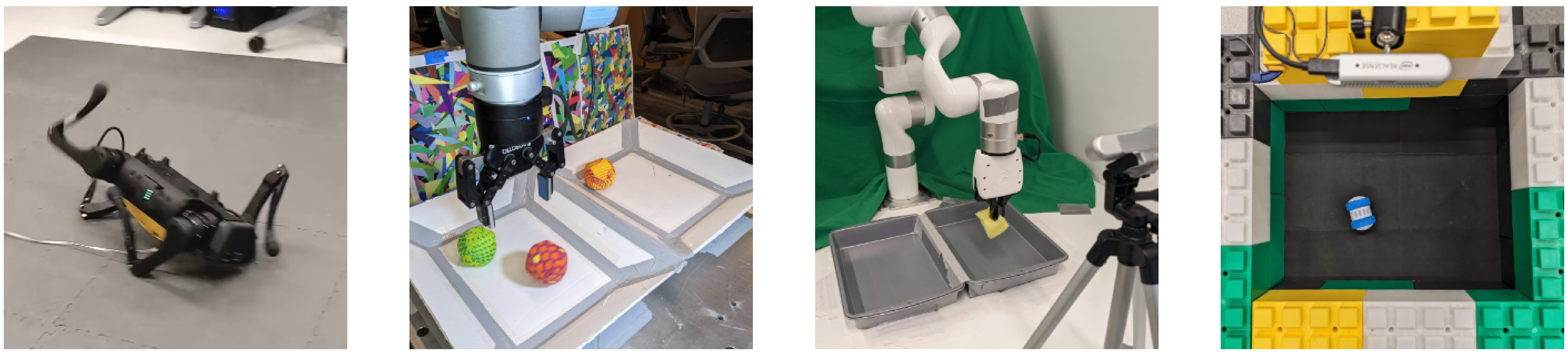


Source: https://dreamrl.github.io/

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.

Wu et al. (2022) DayDreamer: World Models for Physical Robot Learning (arXiv:2206.14176).

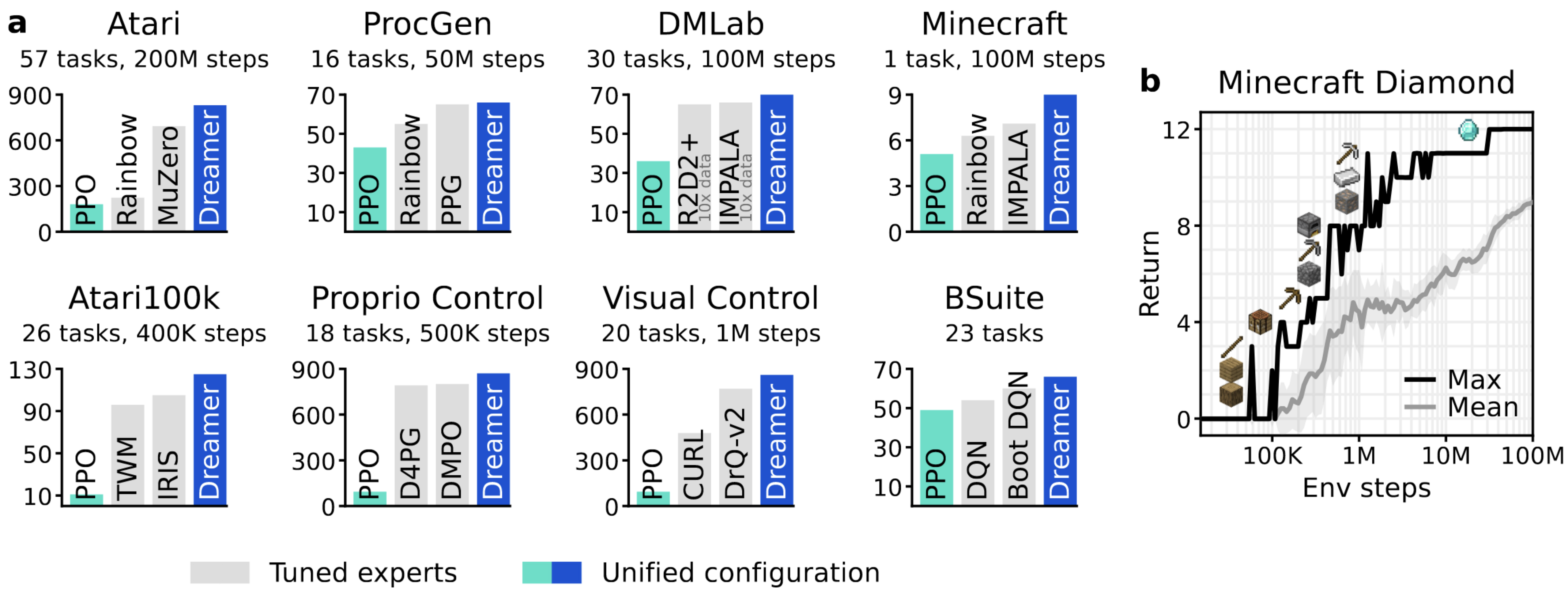
DayDreamer


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

Dreamer v3

- The third iteration of Dreamer established SoTA performance on more than 150 benchmarks.
- It is the first algorithm to collect diamonds in Minecraft from scratch without human data or curricula.

(a) Control Suite **(b)** Atari **(c)** ProcGen **(d)** DMLab **(e)** Minecraft



5 - Temporal difference models - TDM (skipped)

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

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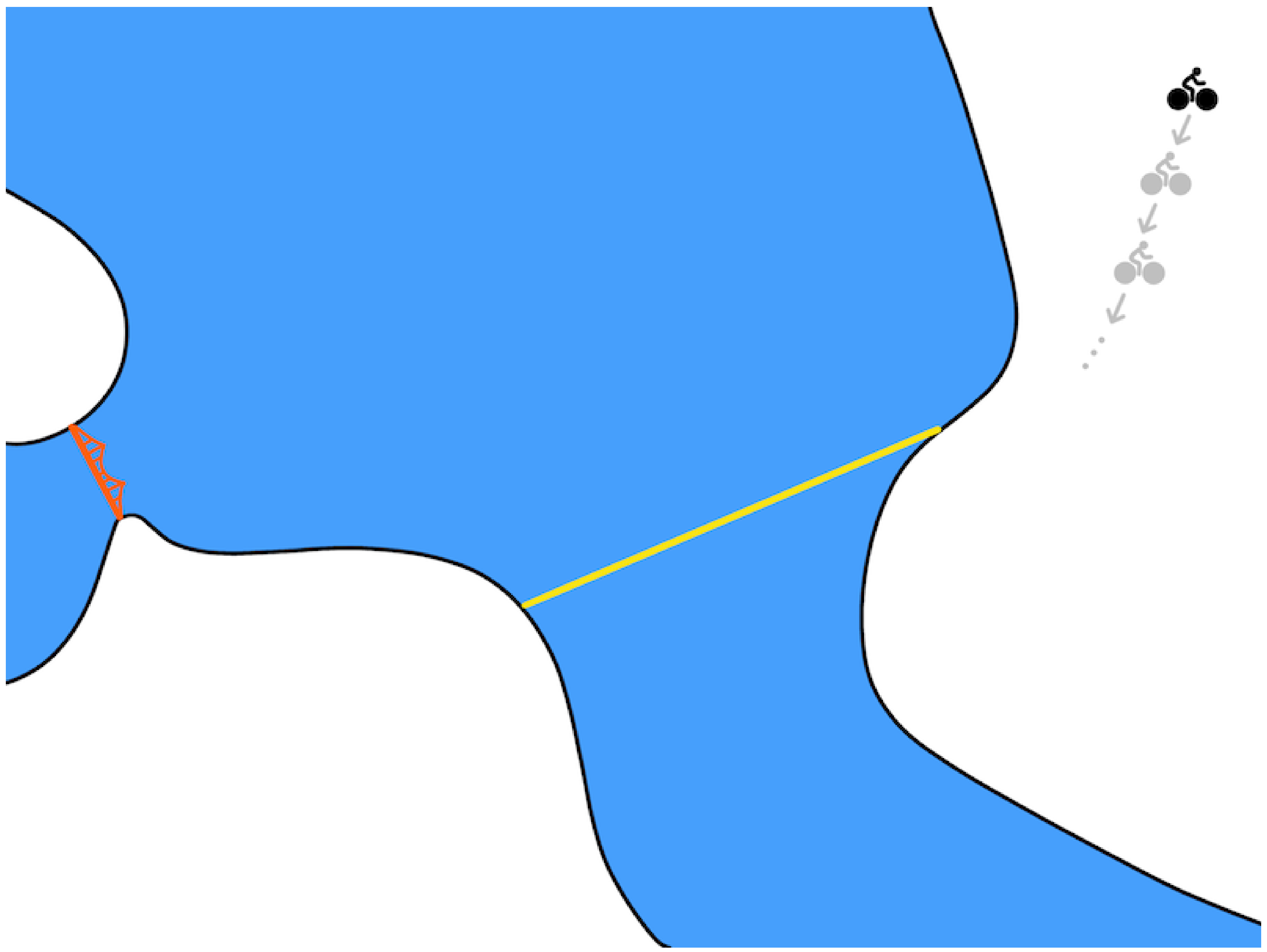
Pong et al. (2018) Temporal Difference Models: Model-Free Deep RL for Model-Based Control. arXiv:1802.09081

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:

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

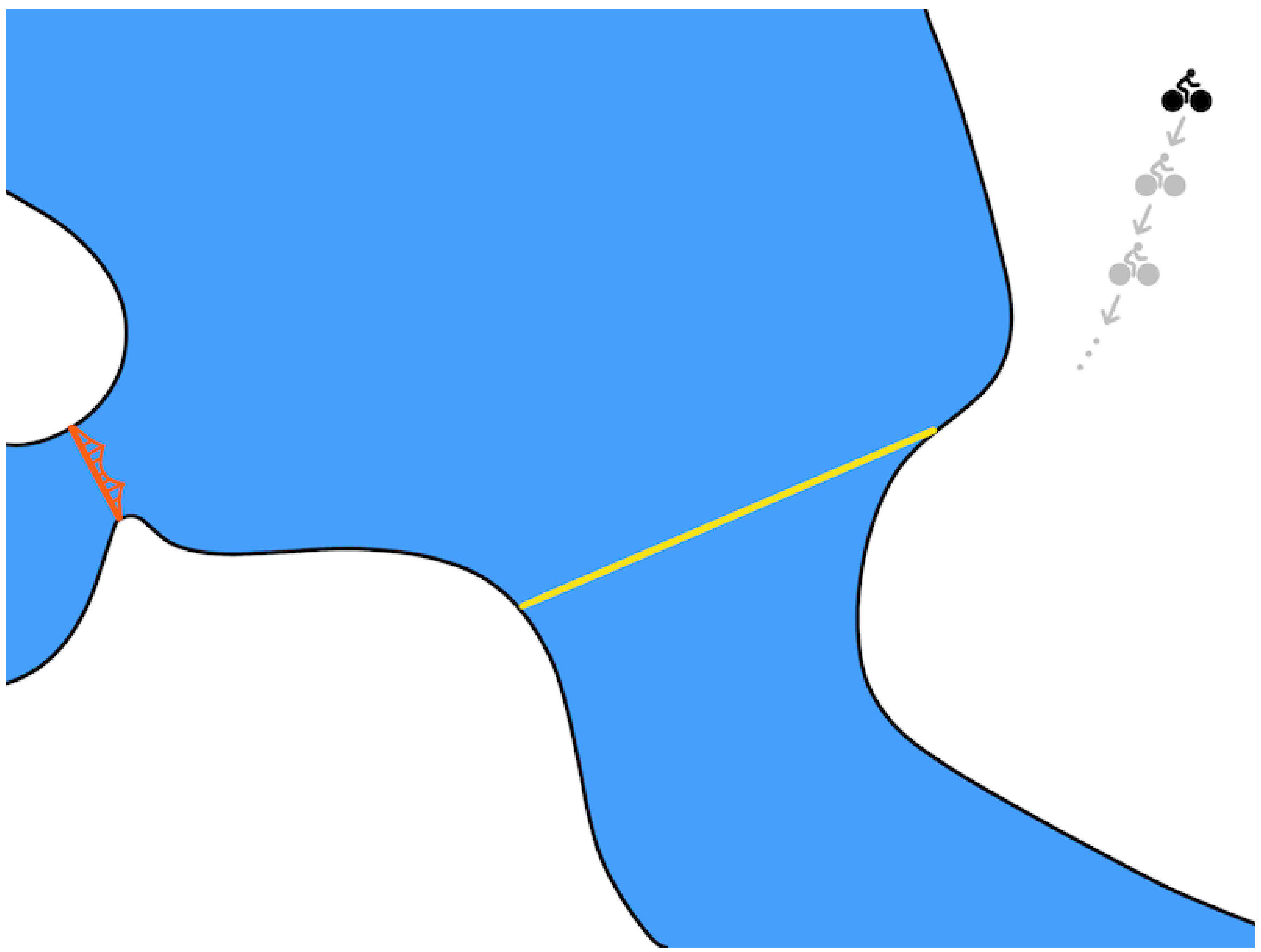
one learns to predict the state achieved in T steps using the current policy:

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

- Planning and acting occur at different time scales.

TDM

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



- 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:

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

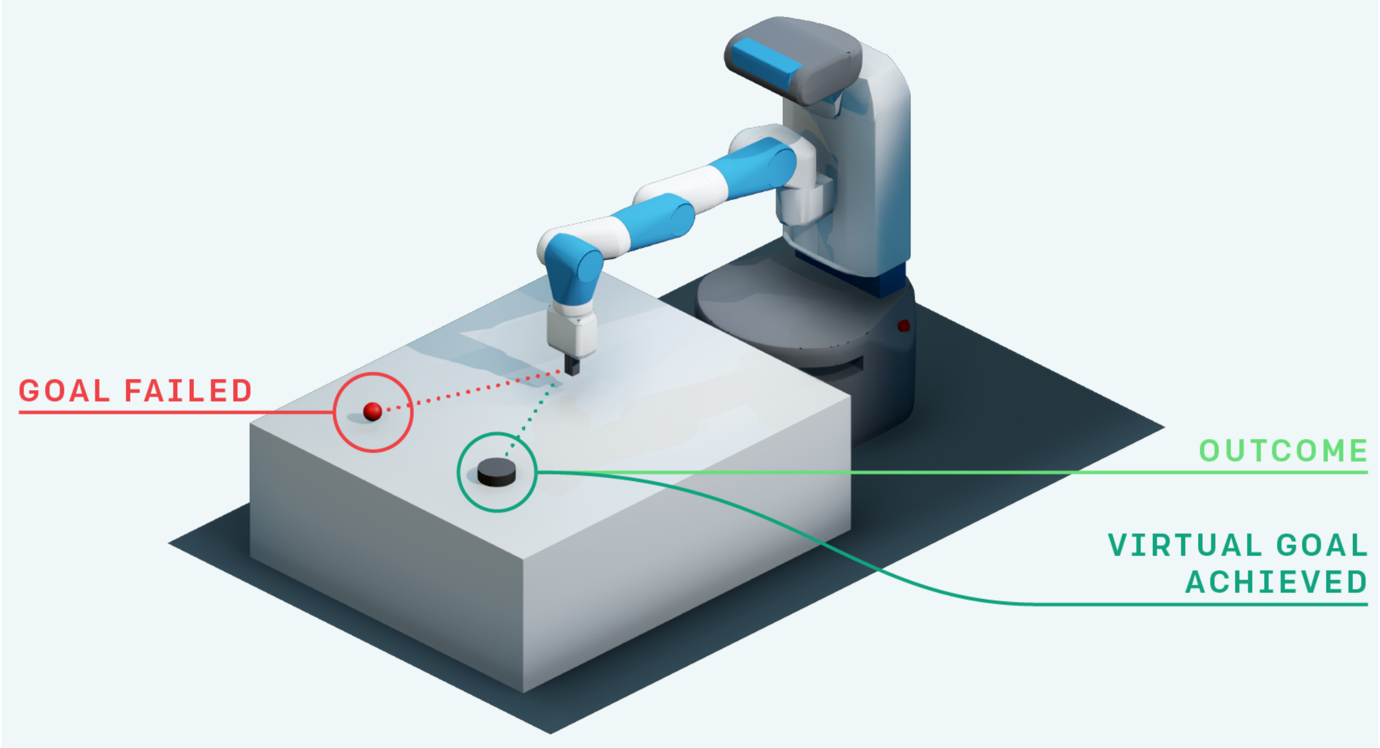
Source: https://bairblog.github.io/2018/04/26/tdm/

- 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.

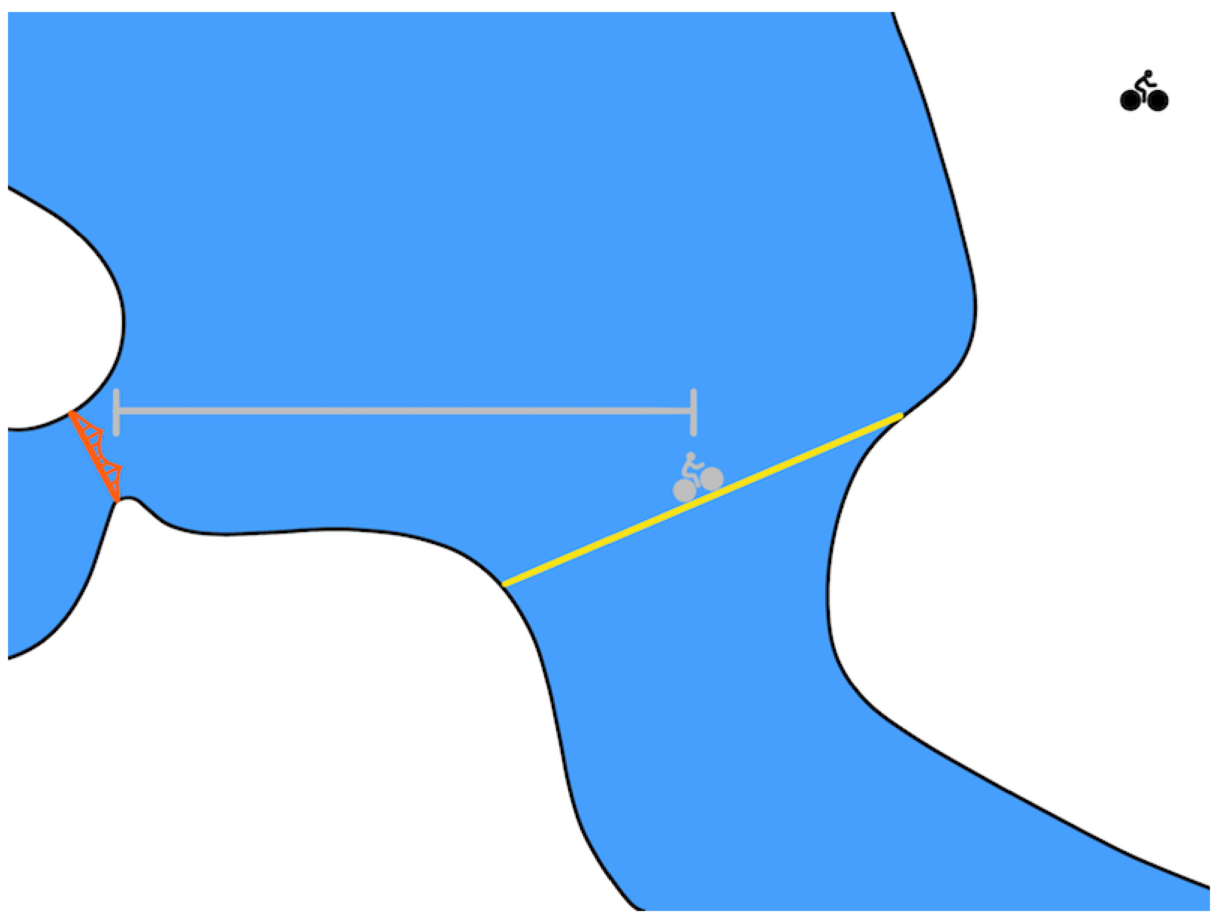


Source: https://openai.com/blog/ingredients-for-robotics-research/

- 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:

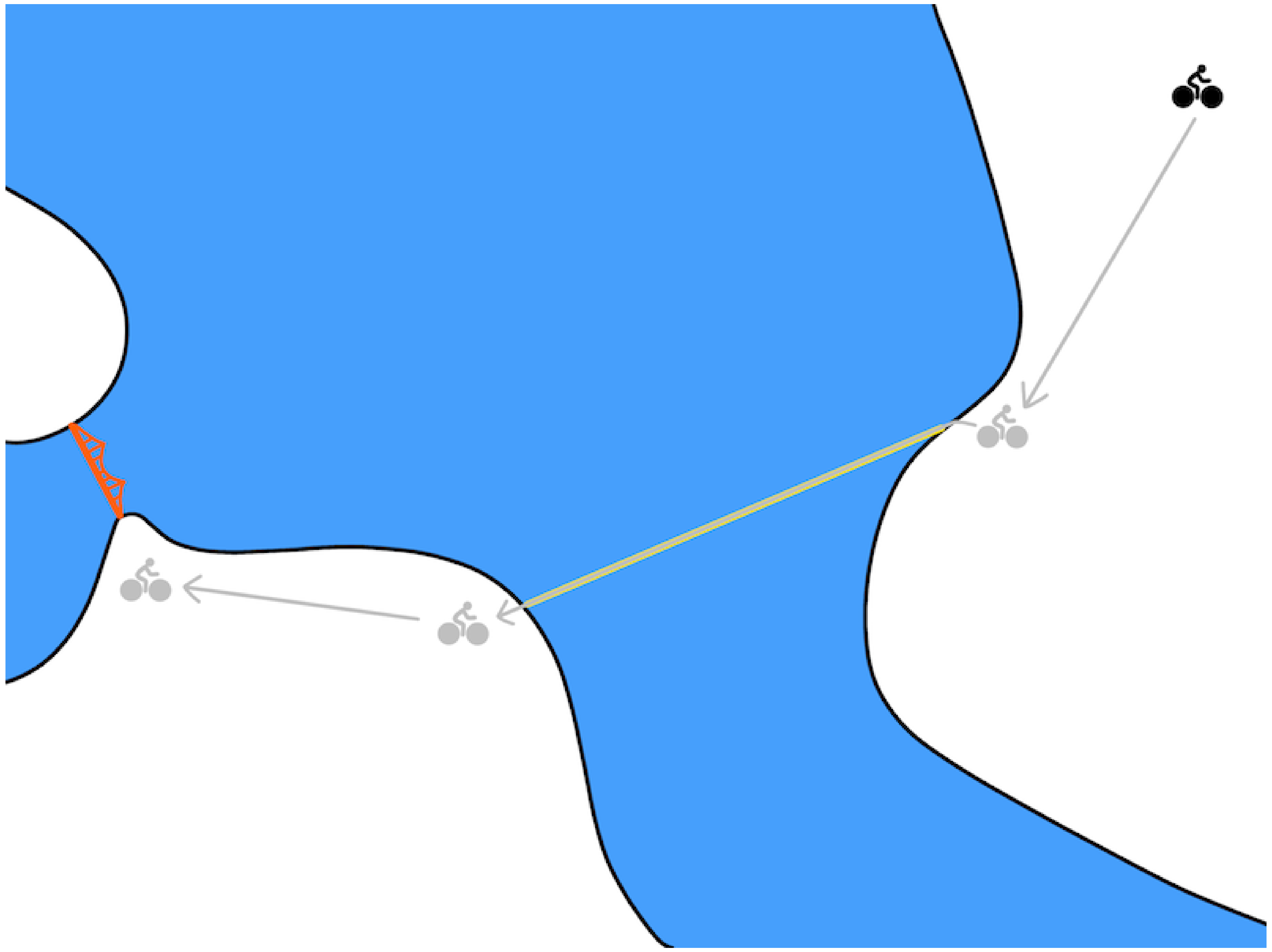
$$a^* = \arg\max_{a_t} \, r(s_{t+T}, a_{t+T}, s_{t+T+1})$$

- 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**:

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

- 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.

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

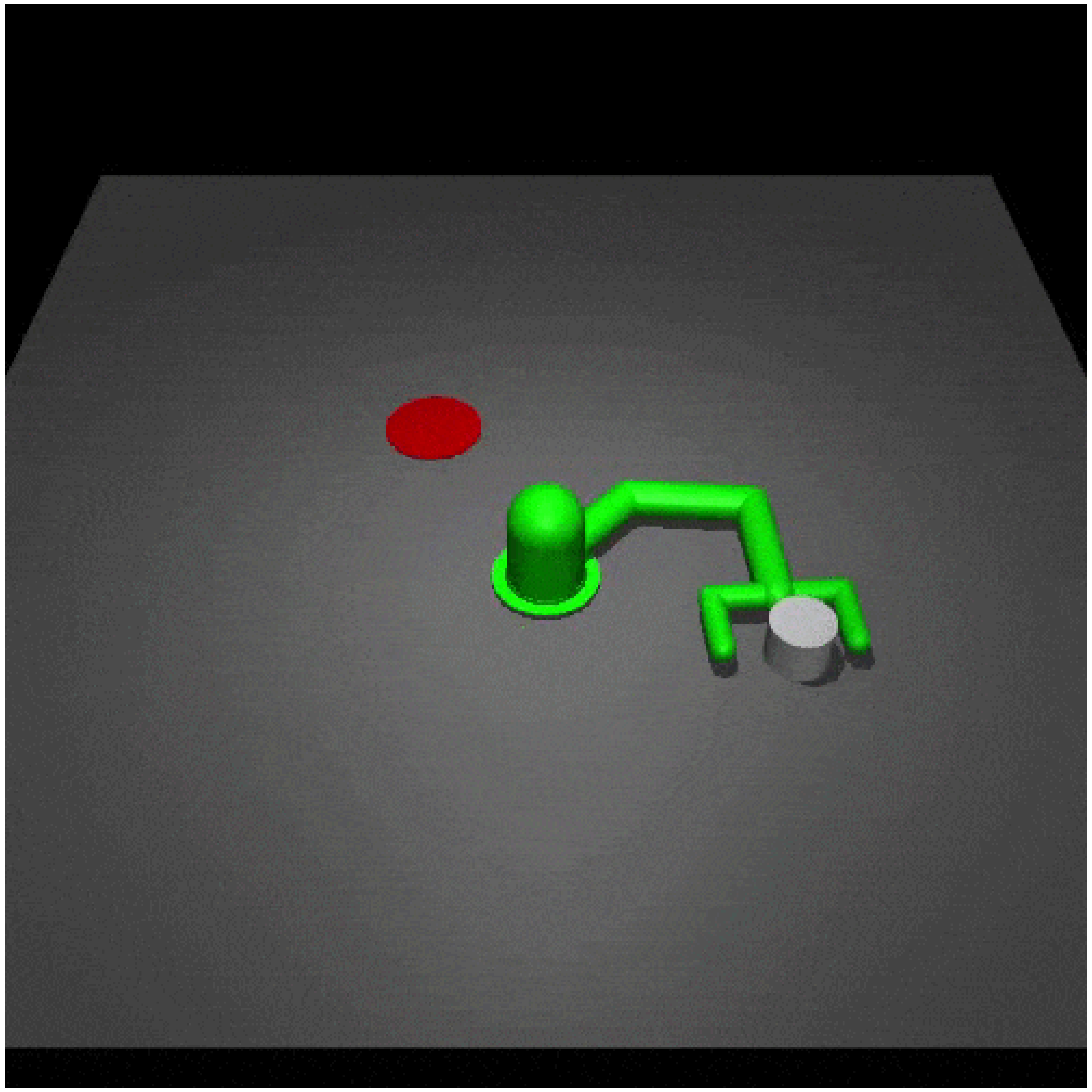
- The actor uses MPC planning to iteratively select actions that bring us closer to the goal in T steps:

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

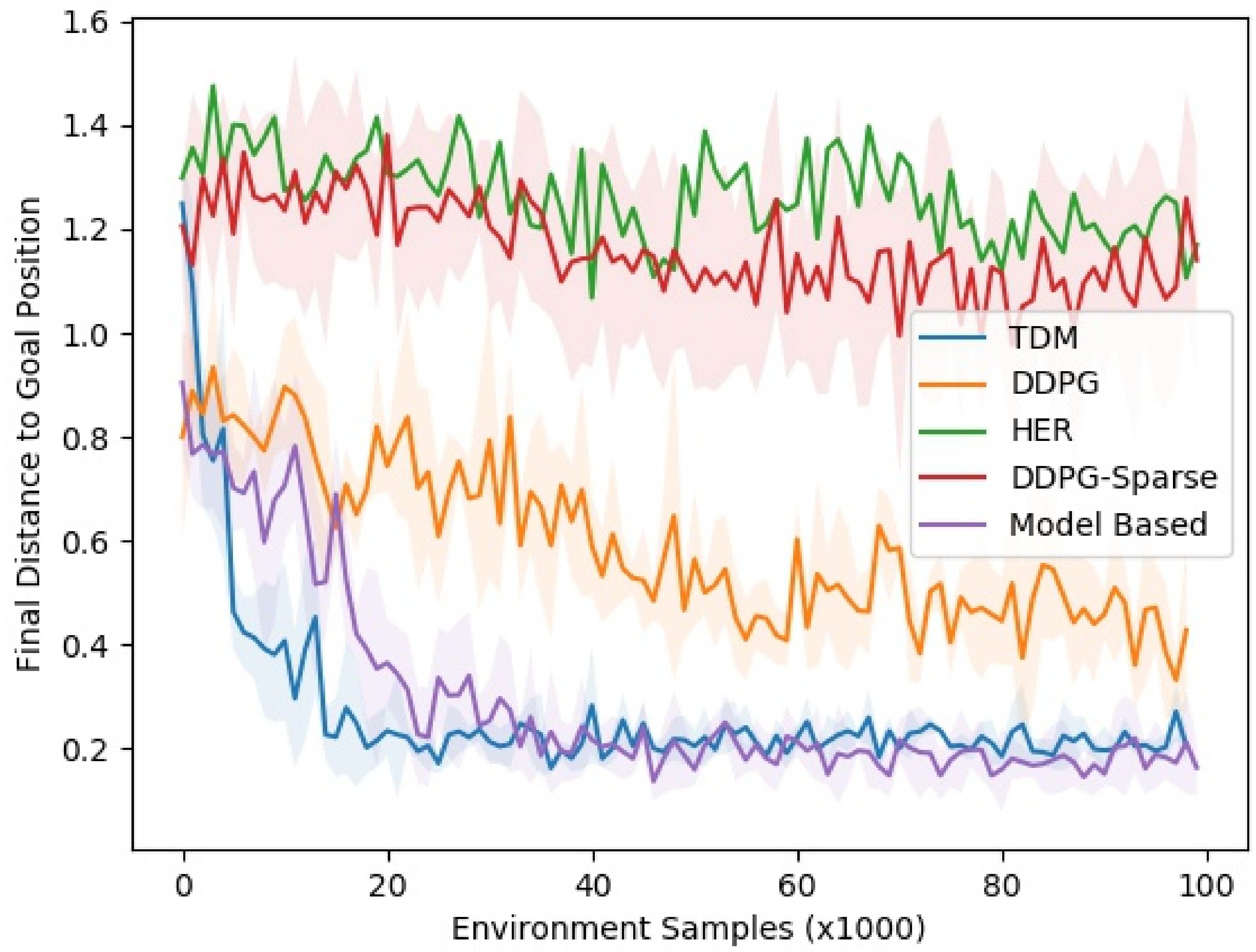
- The argmax can be estimated via sampling.
- TDM is a model-based method in disguise: it does predict the next state directly, but how much closer it will be to the goal via Q-learning.

TDM results

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



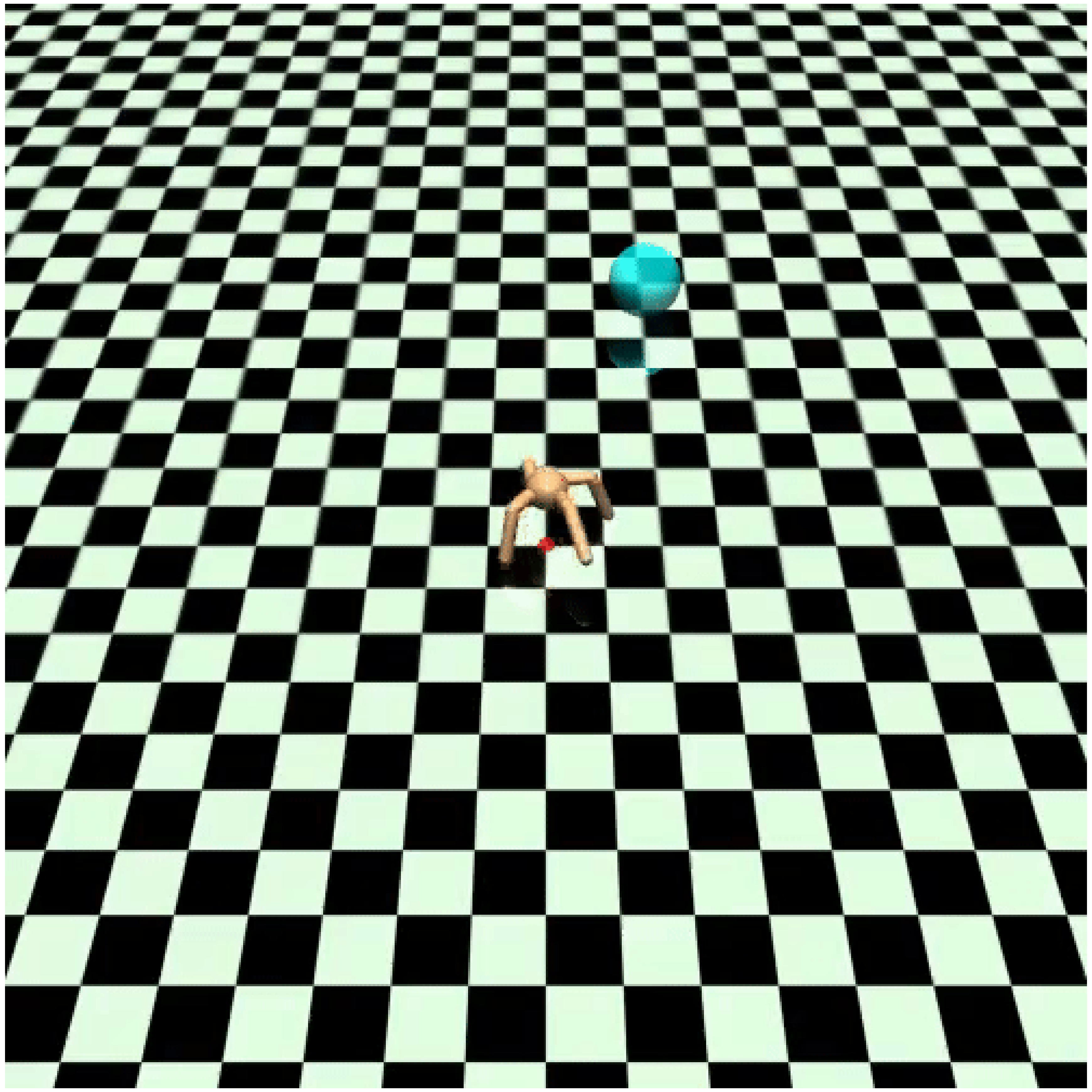
- Model-free methods have a much higher sample complexity.
- TDM learns much more from single transitions.



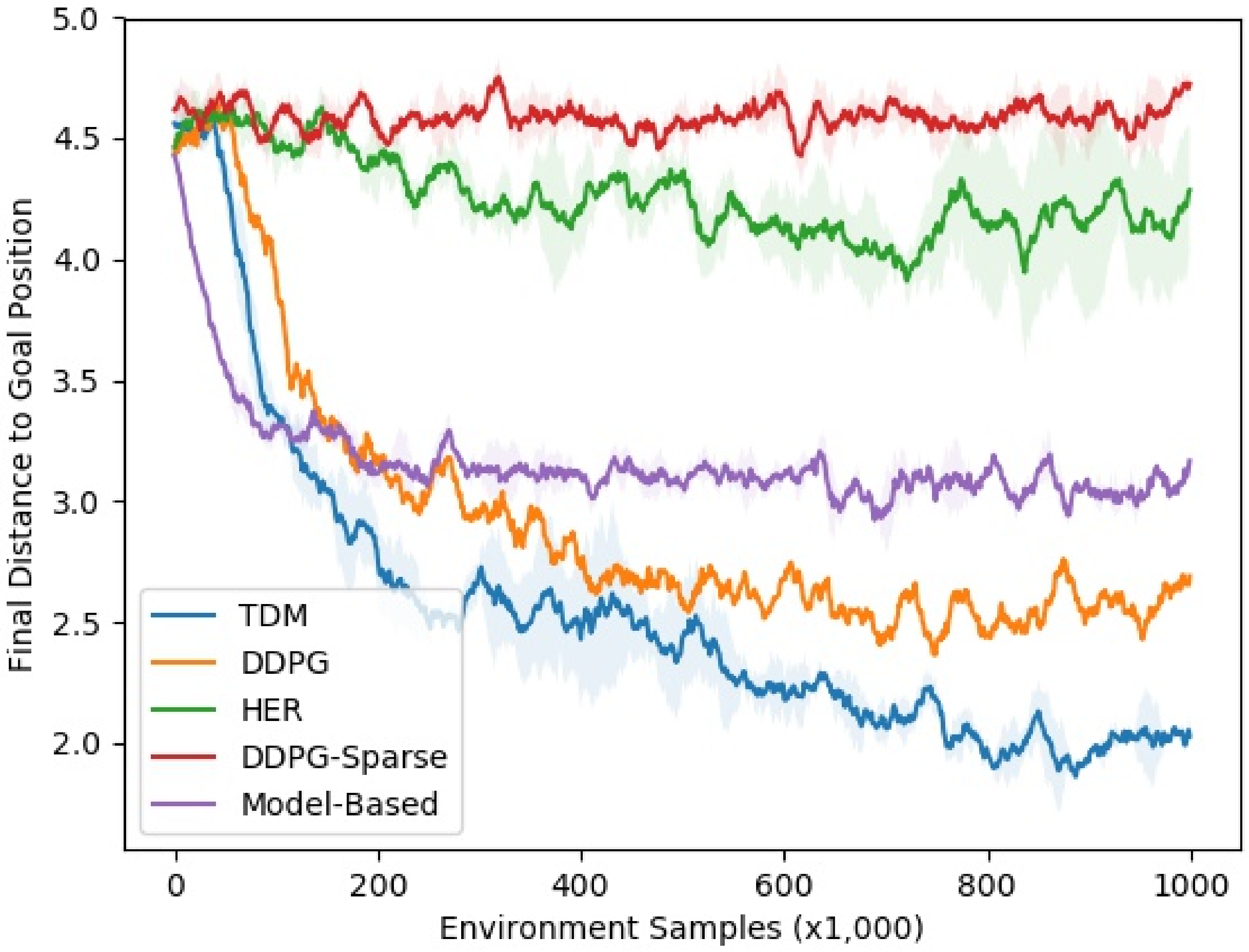
Source: https://bairblog.github.io/2018/04/26/tdm/

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/

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