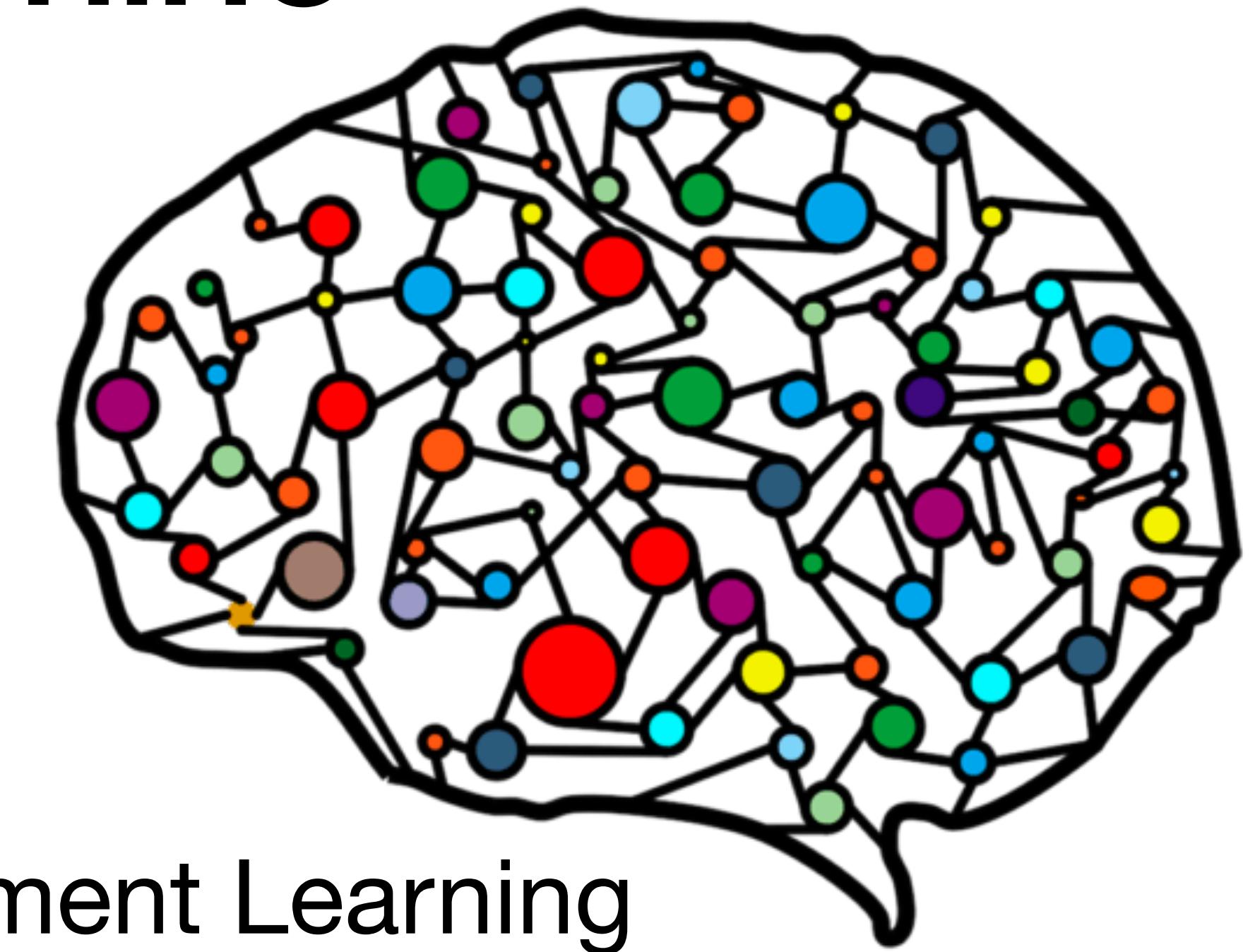


General Principles of Human and Machine Learning



Lecture 5: Advances in Reinforcement Learning

Dr. Charley Wu

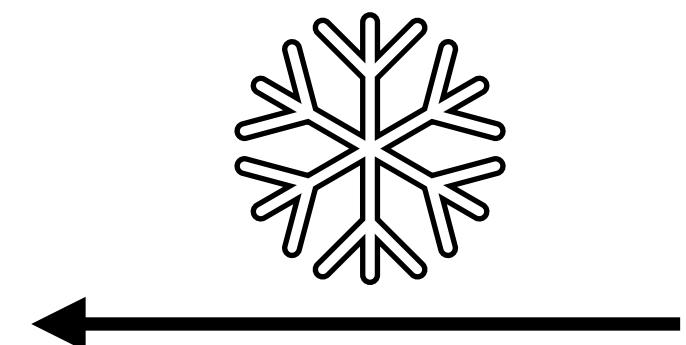
<https://hmc-lab.com/GPHML.html>

Schedule

Week 6:	Guest lecturer: Alexandra Witt	Nov 19: Social learning	Nov 20	Alex	Witt et al., (2024)
Week 7:	Guest lecturer: Dr. David Nagy	Nov 26: Compression and resource constraints	Nov 27	David	Nagy et al., (under review)
Week 8:		Dec 3: Concepts and Categories	Dec 4	Hanqi	Murphy (2023)
Week 9:		Dec 10: Supervised and Unsupervised learning	Dec 11	Hanqi	Bishop (Ch. 4)
	Holiday break				
Week 10:		Jan 14: Function learning	Jan 15	Alex	Wu, Meder, & Schulz (2024)
Week 11:		Jan 21: No Lecture	Jan 22: No Tutorial		
Week 12:		Jan 28: Language and semantics	Jan 29	TBD	Kamath et al., (2024)
Week 13:		Feb 4: General Principles	Feb 5	Charley	Gershman (2023)

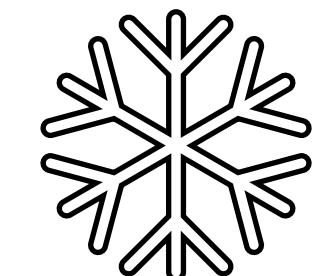
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← Swapped ↘

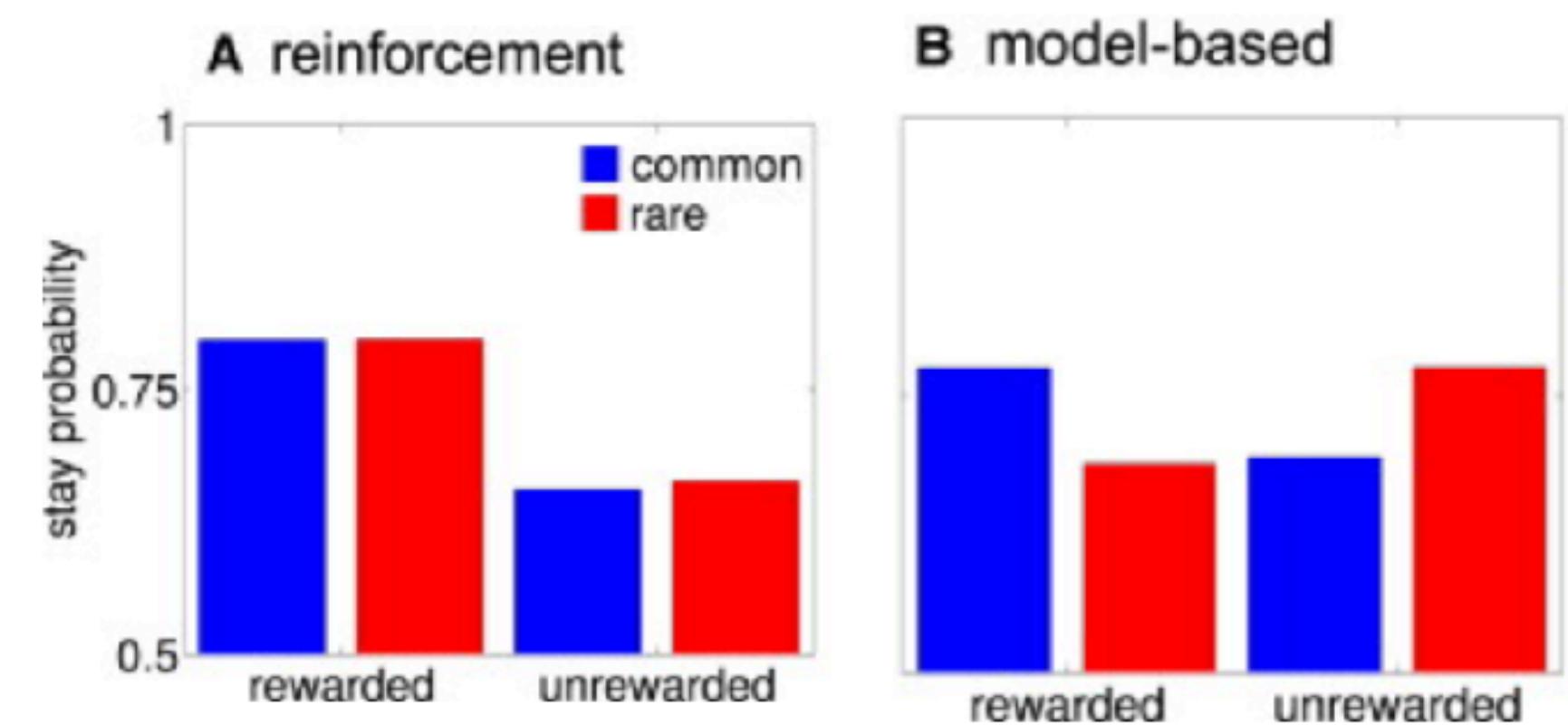
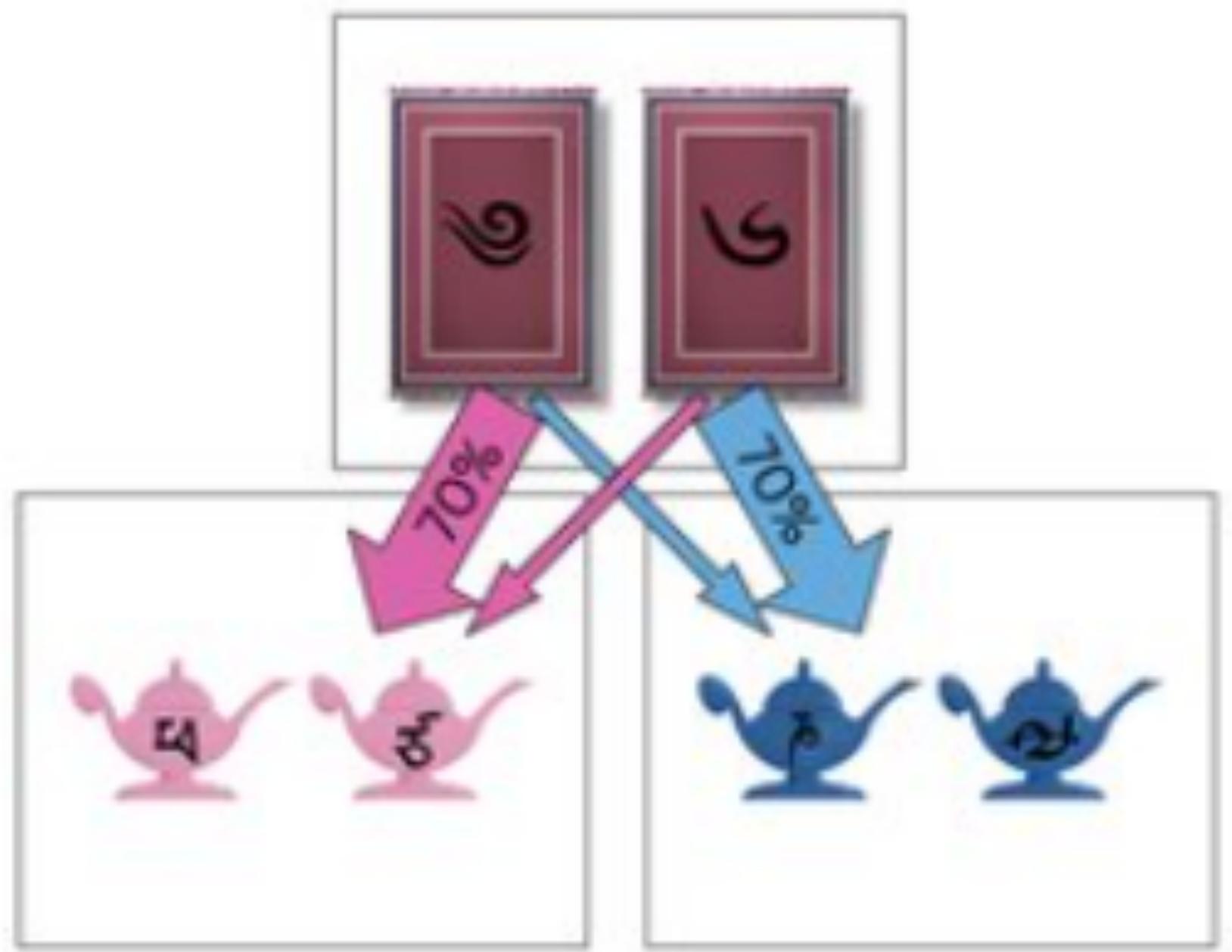
Exam times

Exam 1	13:00-15:00 21.02.2025 Hörsaal 1 F119 (SAND)
Exam 2	12:00-14:00 11.04.2025 (to be confirmed)



Clarification

- Two-step tasks
 - Transitions are a property of the environment and the participants choice
 - The participant chooses  or 
 - But then probabilistically (common=70% vs. rare = 30%), transitions to either pink or blue on the 2nd step
- The key takeaway is that MF vs MB have different responses to the same outcome
 - MF: If rewarded —> stay
if not rewarded —> go
 - MB: depends on whether reward followed a common or rare transition... *you shouldn't expect a rare transition to occur again*
if (common & reward | rare & no reward) —> stay
if (common & no reward| rare & reward) —> stay

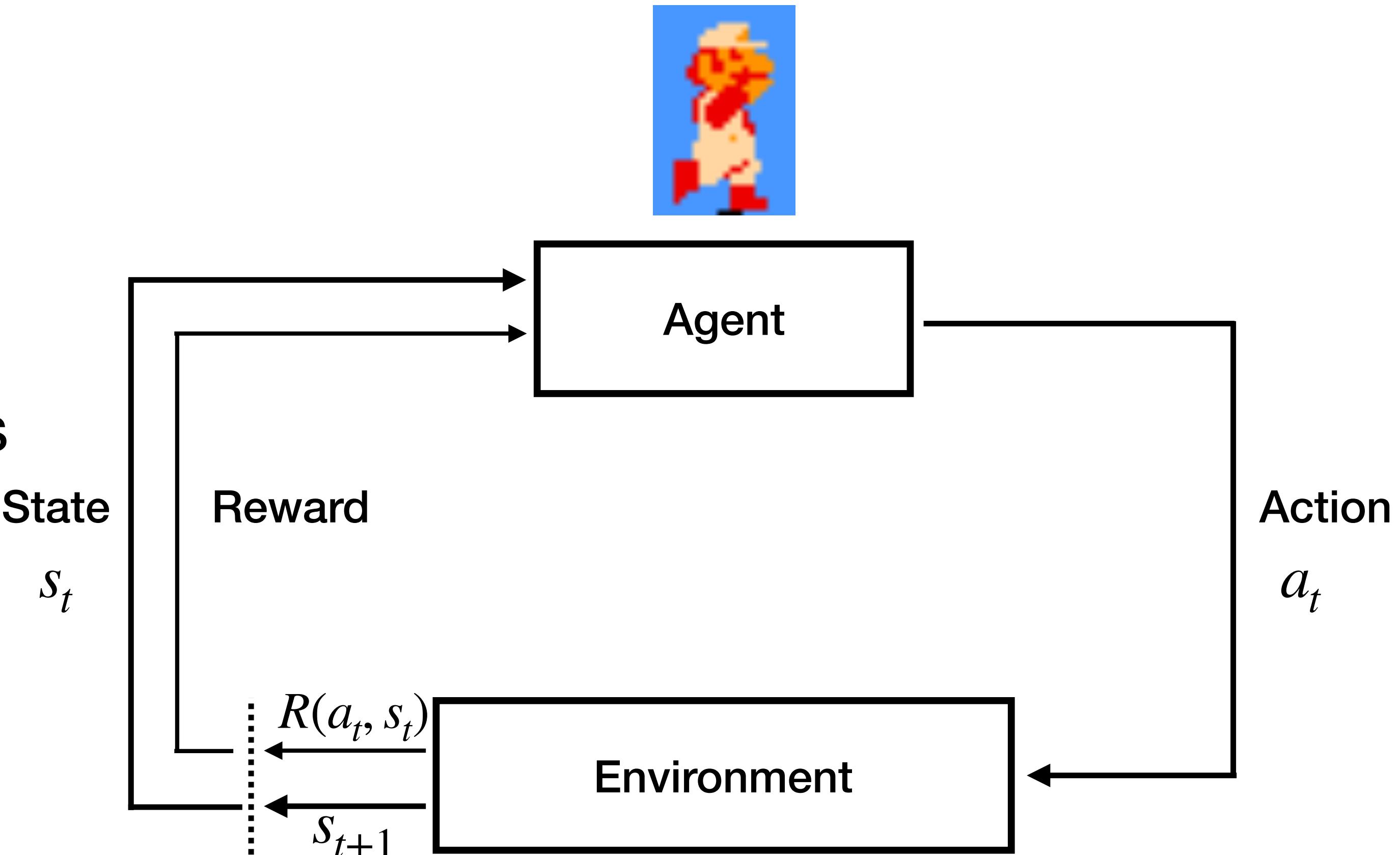


Last week...

Reinforcement Learning

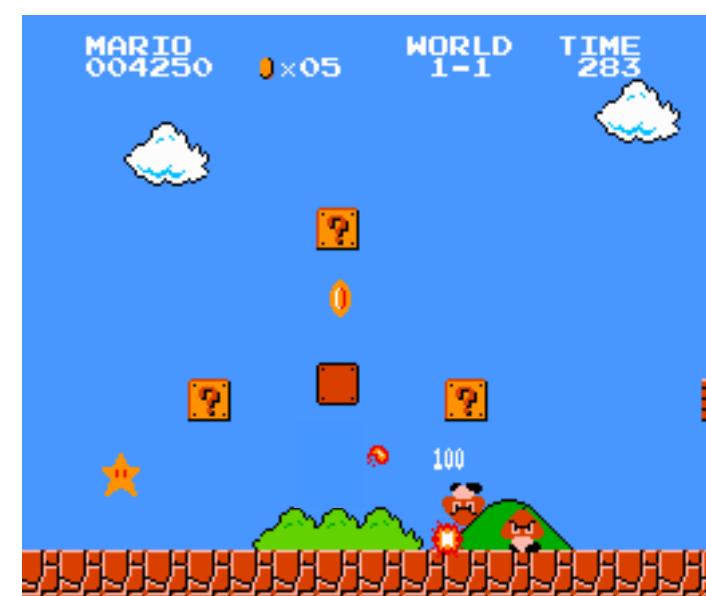
The Agent:

- Selects actions a_t
- Receives feedback from the environment in terms of new states s_{t+1} and rewards $R(a_t, s_t)$



The Environment:

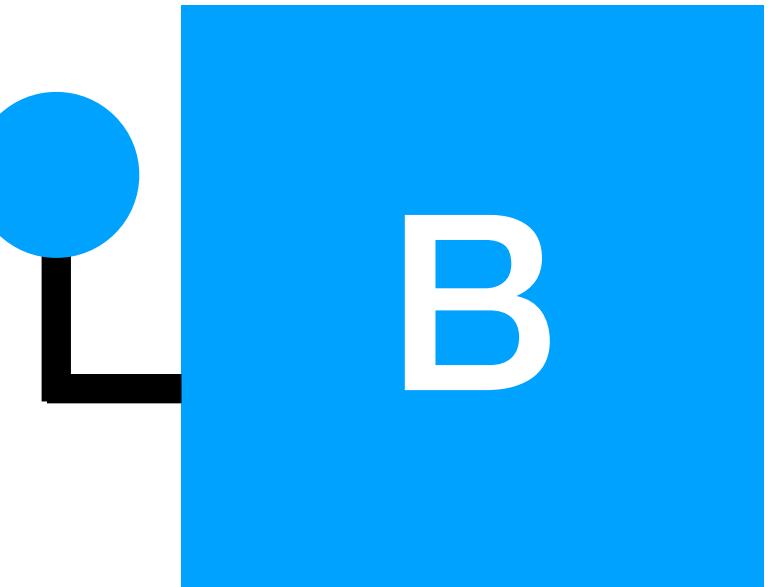
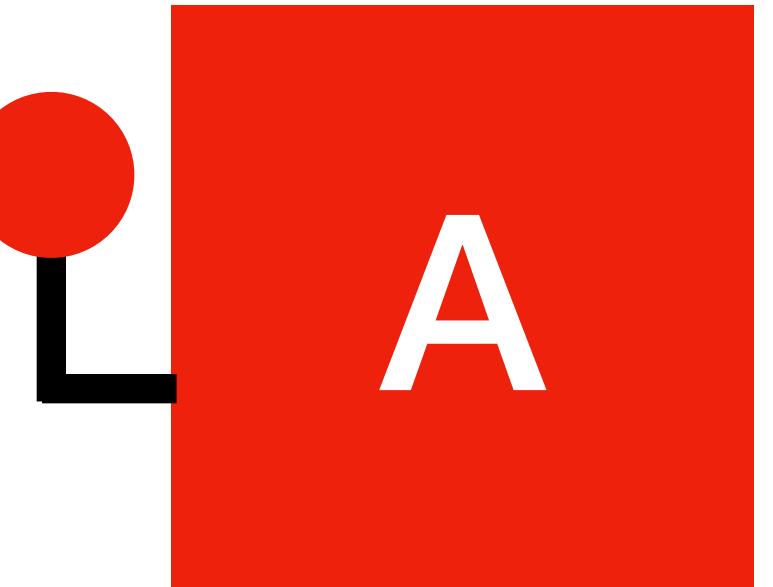
- Governs the transition between states $s_t \rightarrow s_{t+1}$
- Provides rewards $R(a_t, s_t)$



Q-Learning in a bandit task

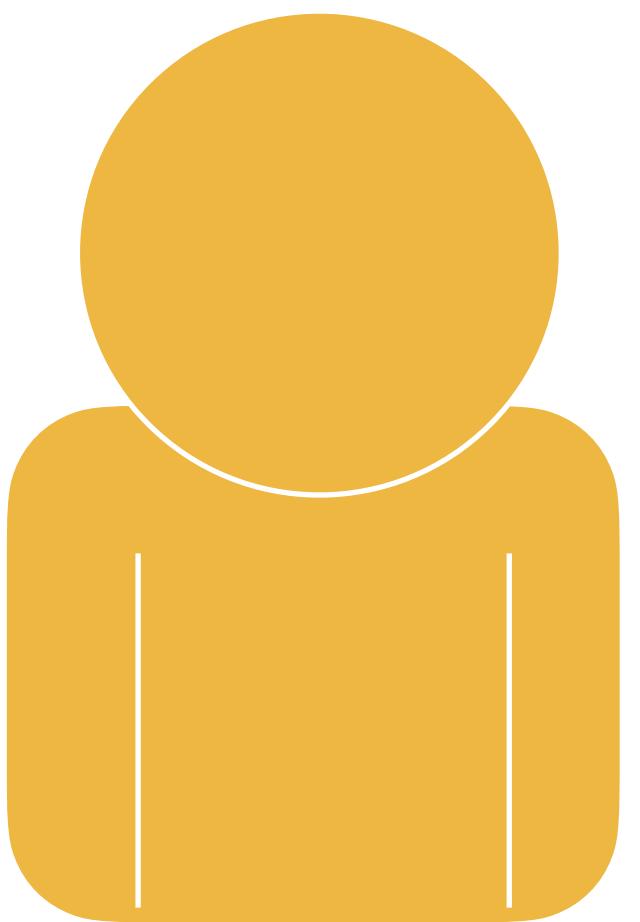
Value learning

$$Q_t(a) \leftarrow Q_t(a) + \eta [r - Q_t(a)]$$



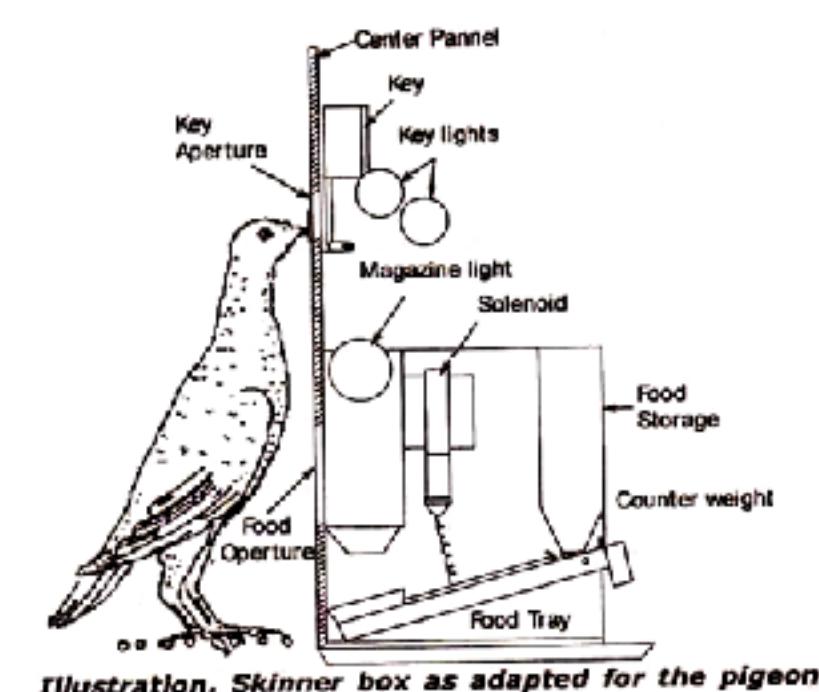
Policy

$$P(a) \propto \exp(Q_t(a)/\tau)$$



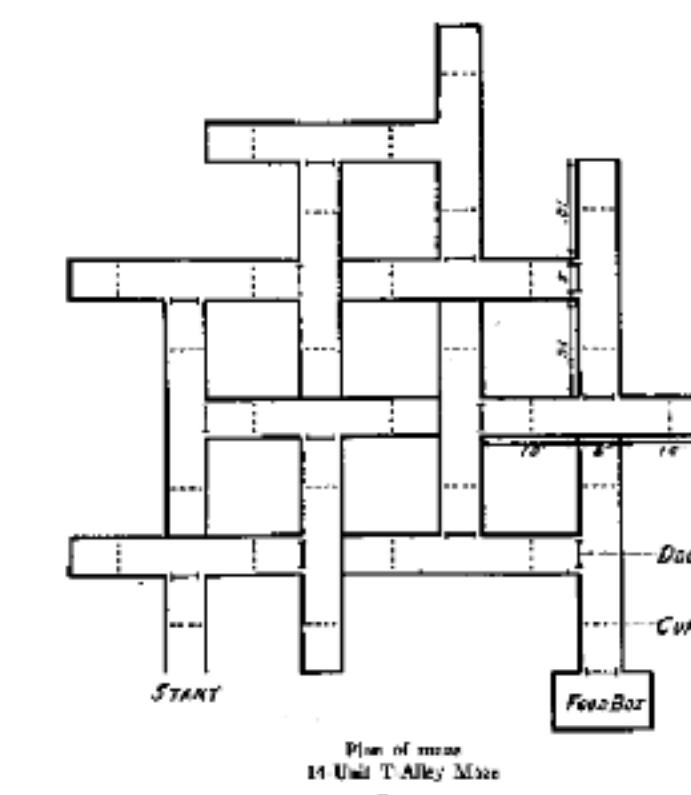
Model-free RL

- Habit
- Cheap
- $Q(s, a)$
- Myopically selecting actions that have been associated with reward



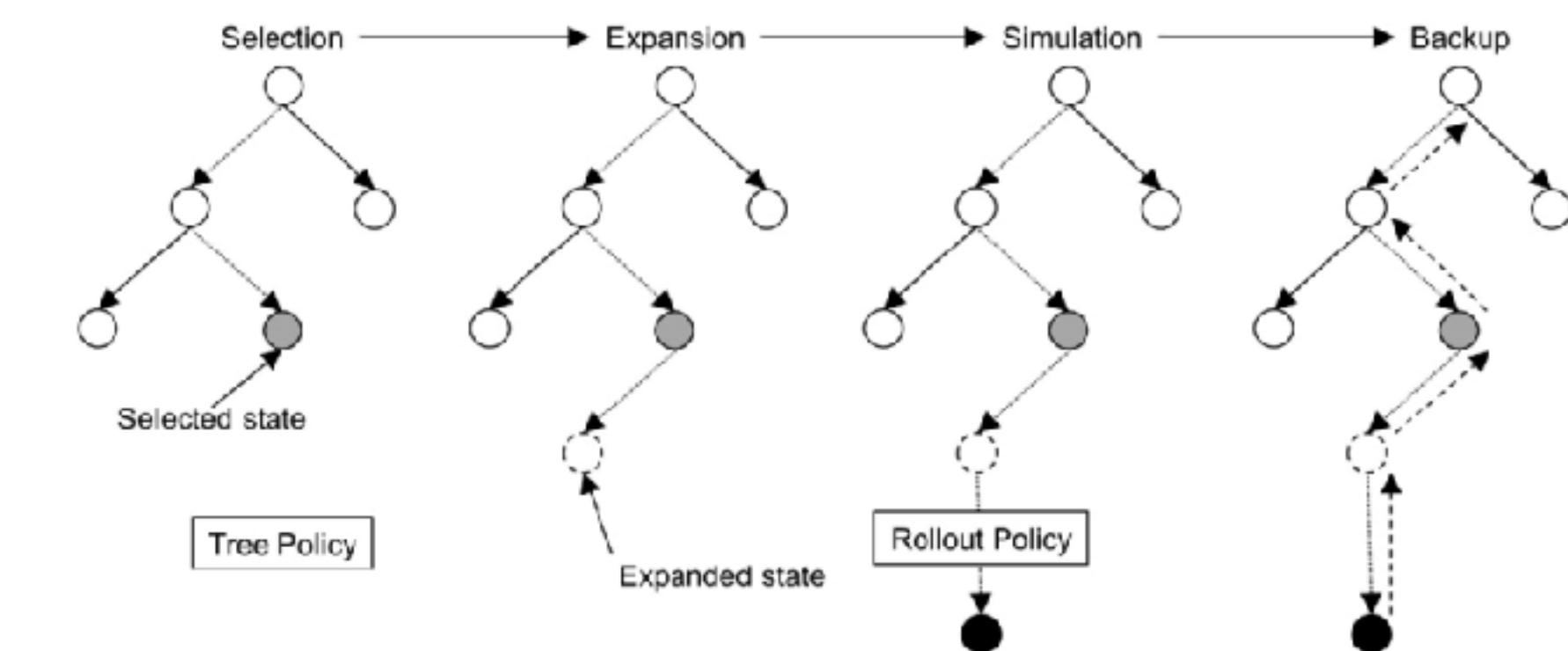
Model-based RL

- Goal-directed
- Computationally costly
- $P(s', r | s, a)$
- Planning and seeking of long term outcomes



(From M. H. Elliott, The effect of change of reward on the maze performance of rats. *Quart. Journ. Psychol.*, 1928, 4, p. 20.)

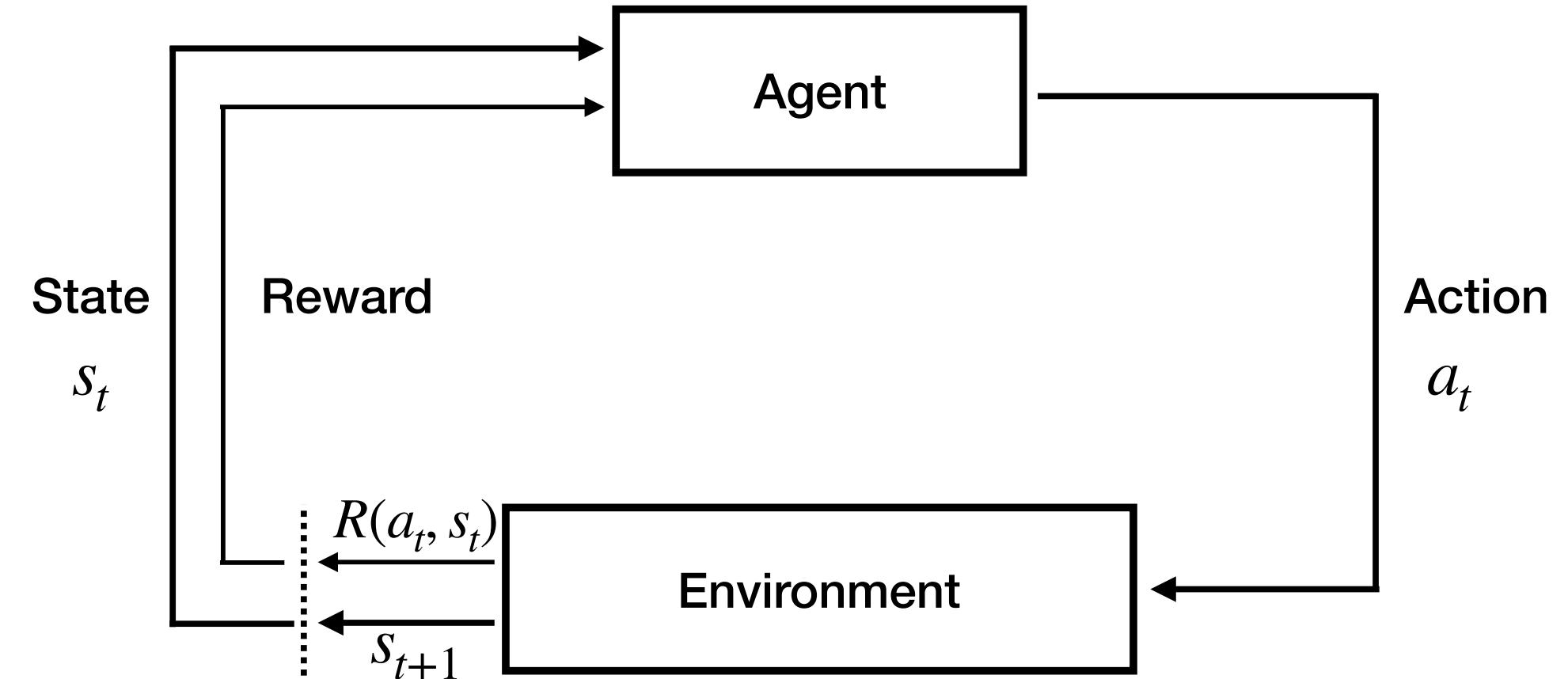
Monte carlo tree search



Today's agenda

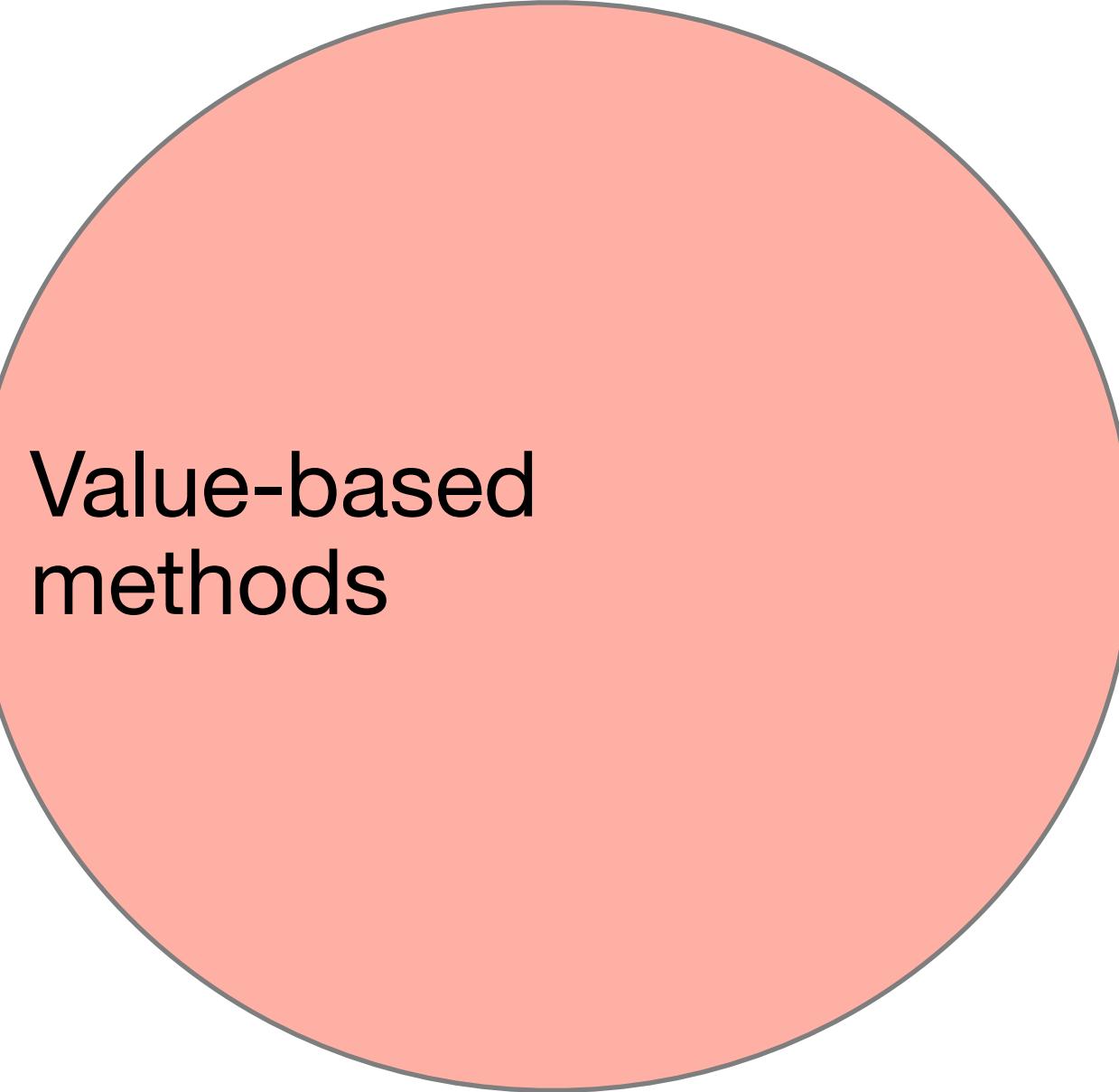
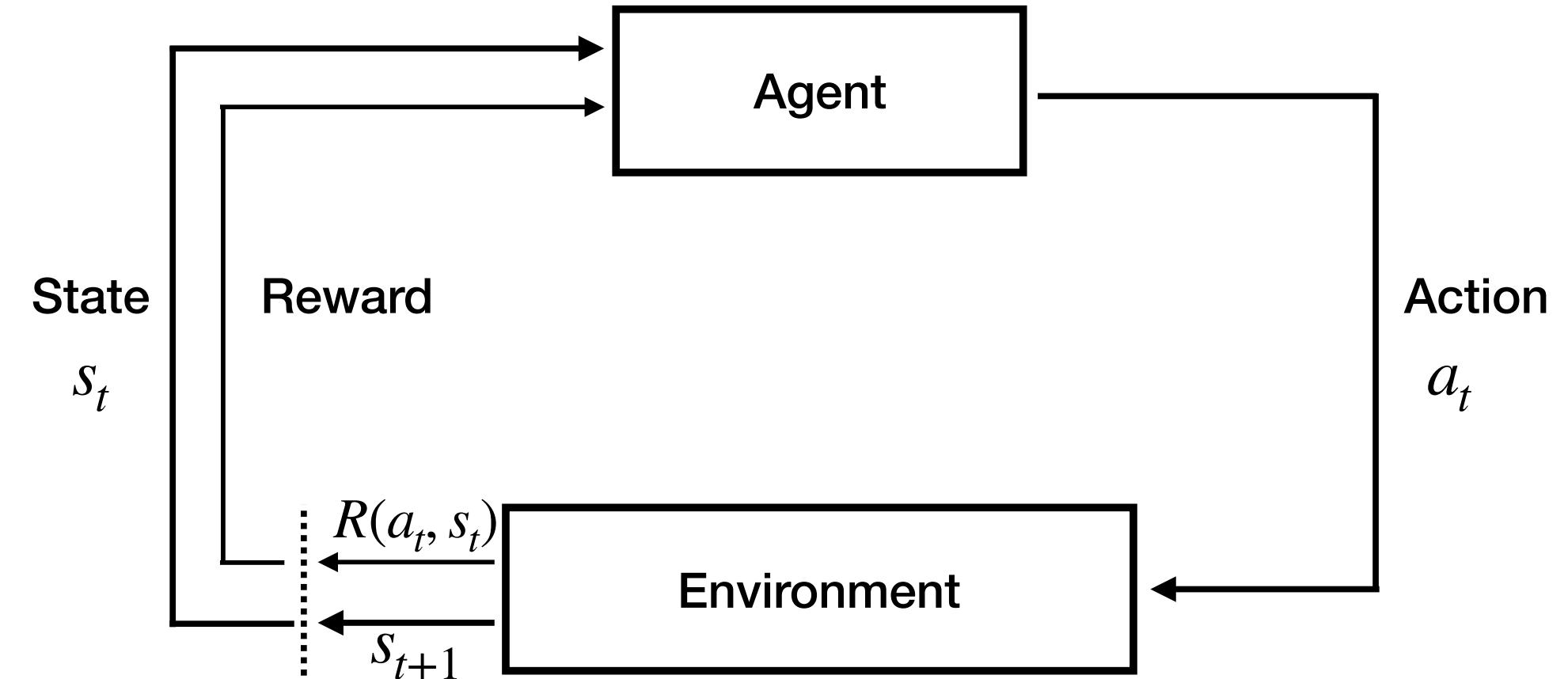
- Advances in ...
 - **Model-free methods**
 - Deep Q-learning, policy gradient & Actor-Critic
 - **Model-based methods**
 - DYNA, World models, & Dreamer
 - **Something in between**
 - Successor representation

Advances in Model-free RL



Advances in Model-free RL

- **Value-based methods**
 - Last week: Value iteration, Q-Learning & TD-learning
 - Problem: what if the state-space is too large to visit?
 - *Deep Q-Learning* for function approximation



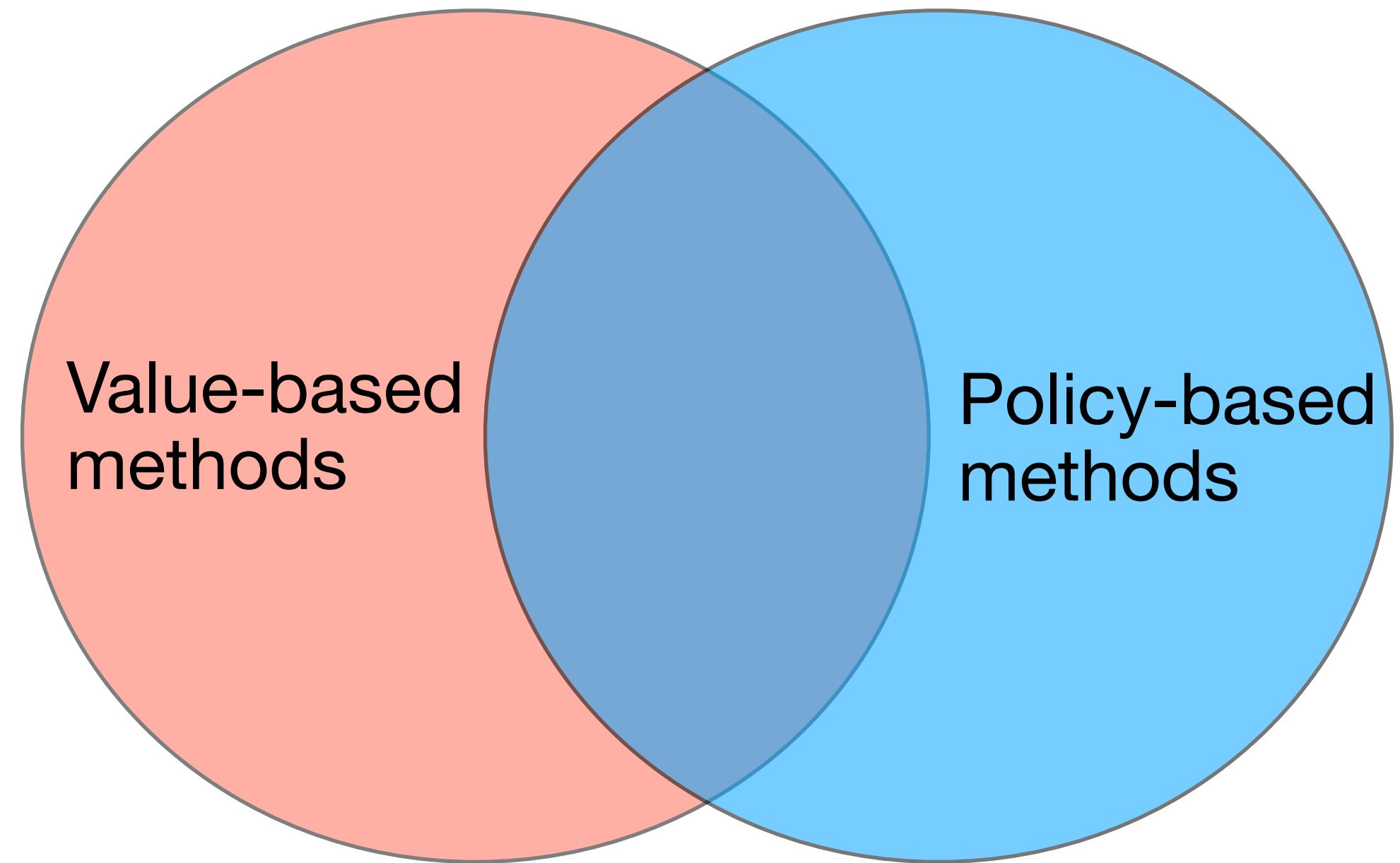
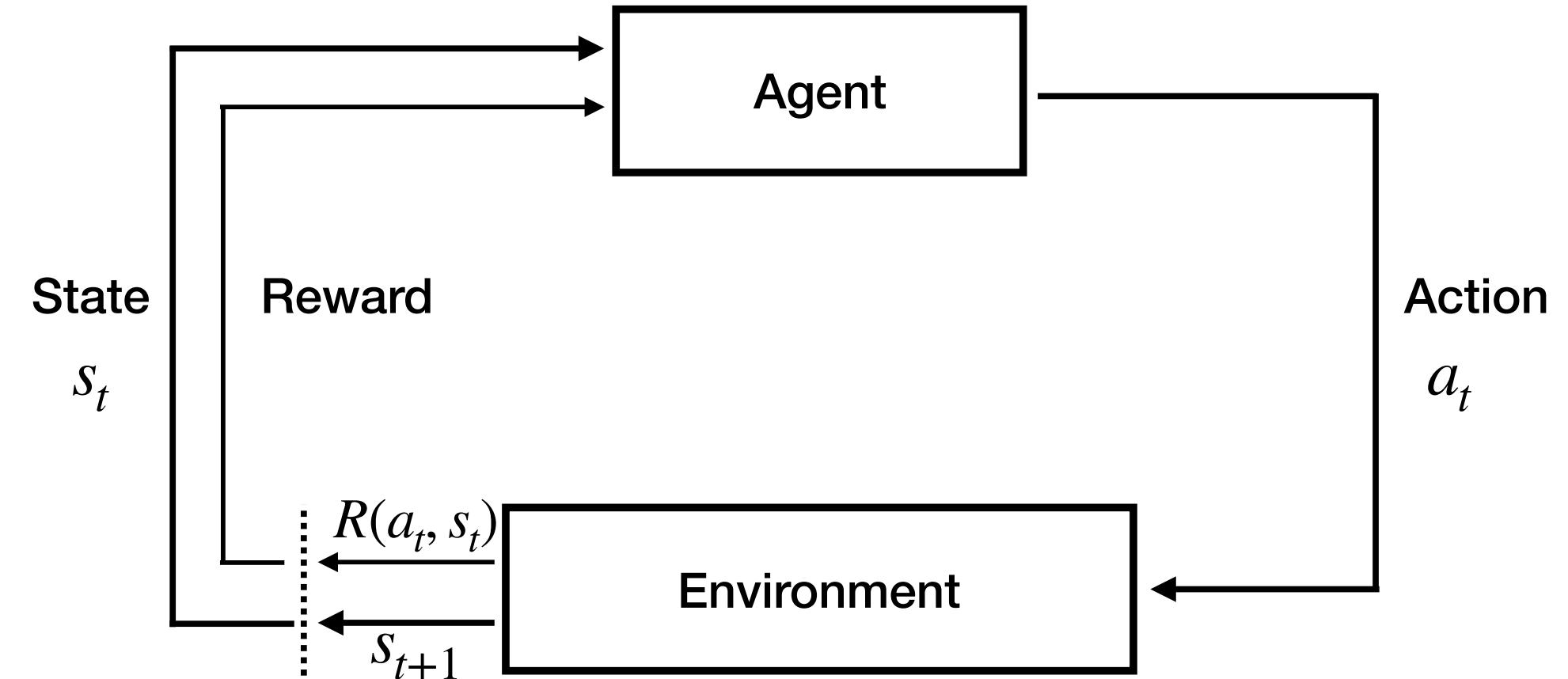
Advances in Model-free RL

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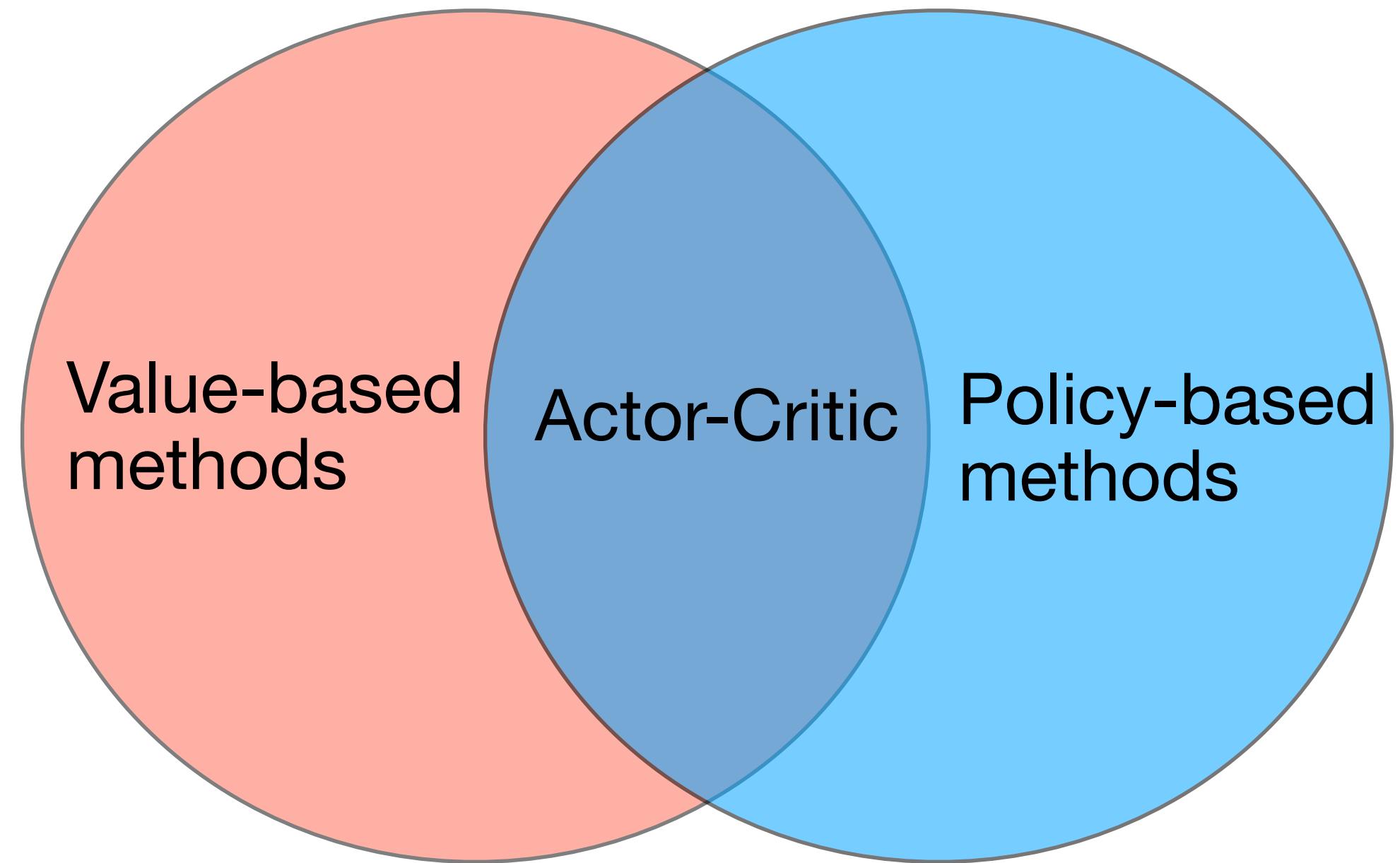
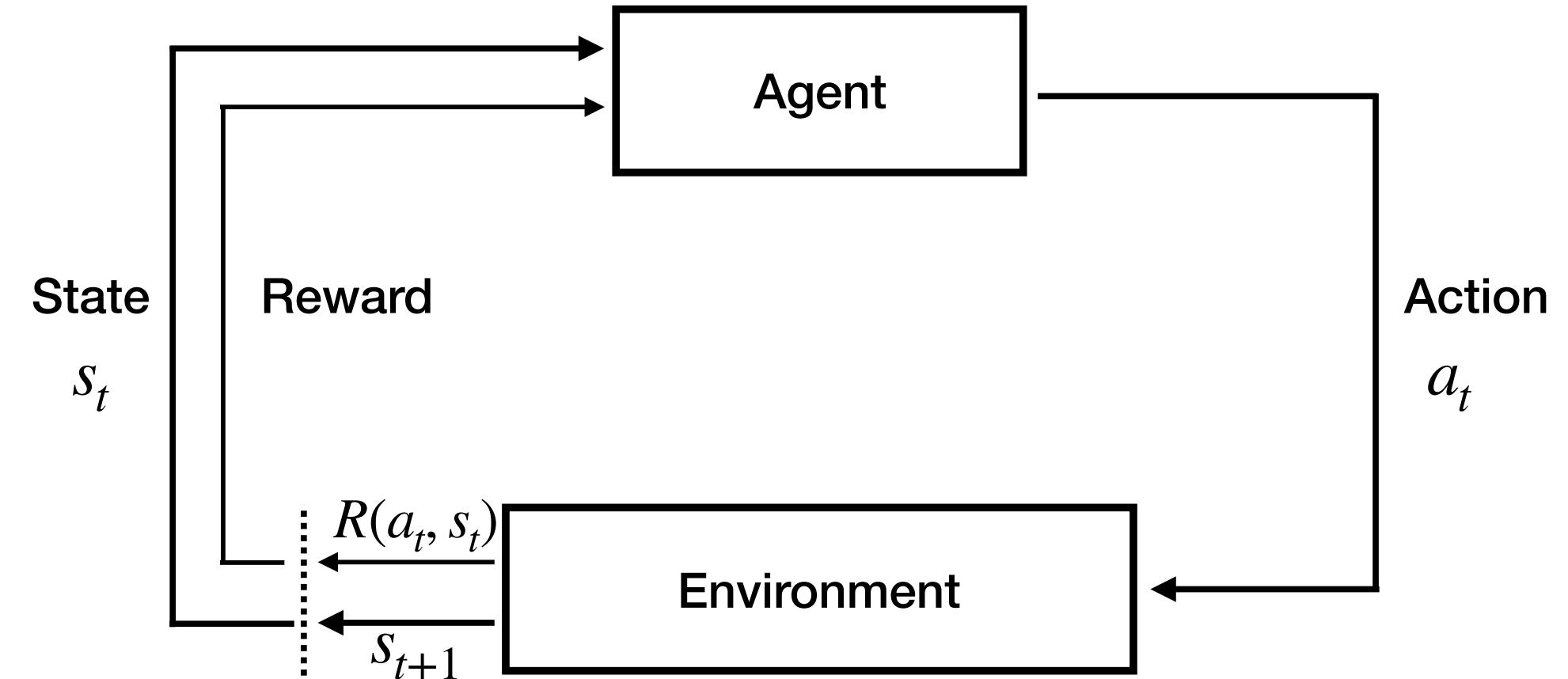
- **Policy-based methods**

- Policy-gradient for directly optimizing a policy



Advances in Model-free RL

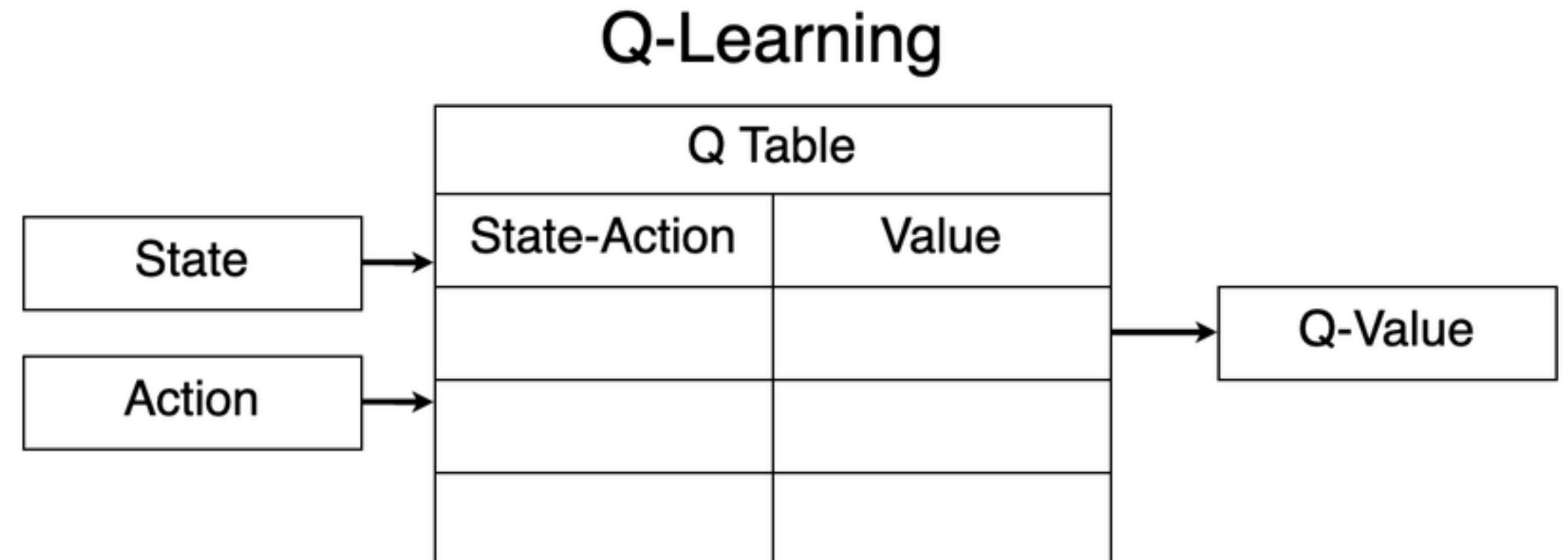
- **Value-based methods**
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 - Problem: what if the state-space is too large to visit?
 - Deep Q-Learning for function approximation
- **Policy-based methods**
 - Policy-gradient for directly optimizing a policy
- **Actor-Critic**
 - Modern version of Policy-iteration:
Value \longleftrightarrow Policy



Deep Q-learning

Tabular methods:

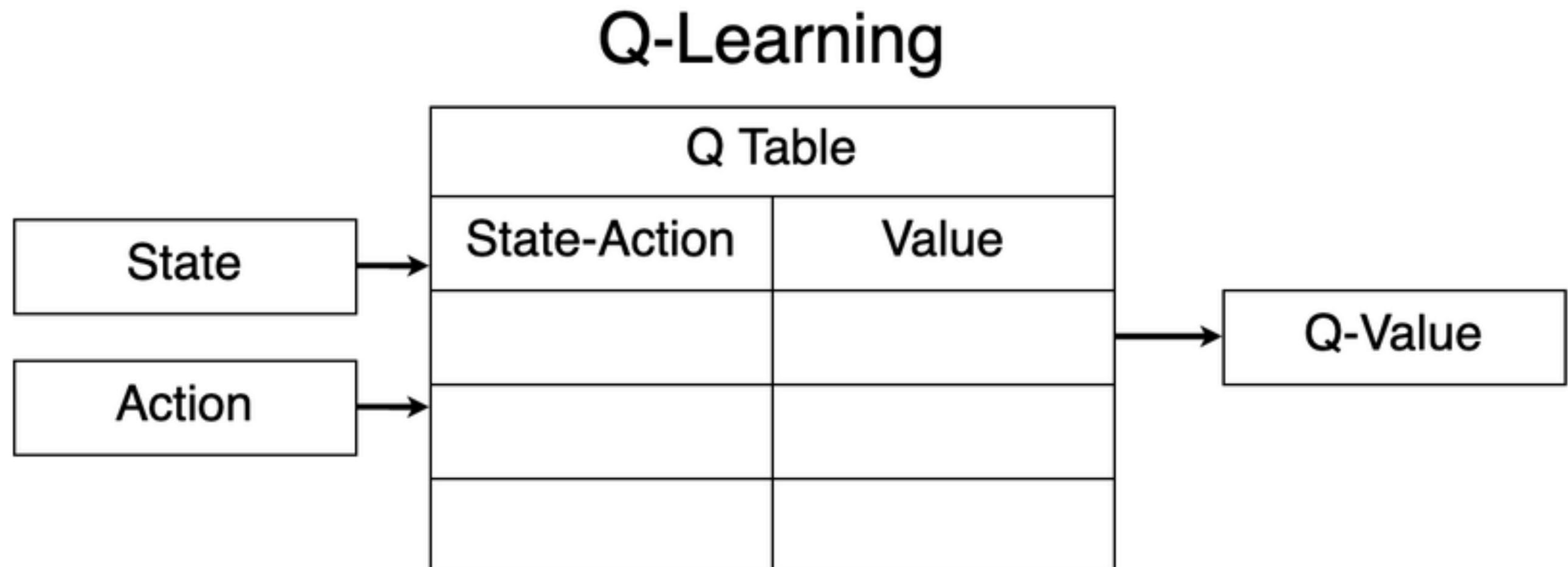
- Q-Learning: learn Q-values by updating a look-up table



Deep Q-learning

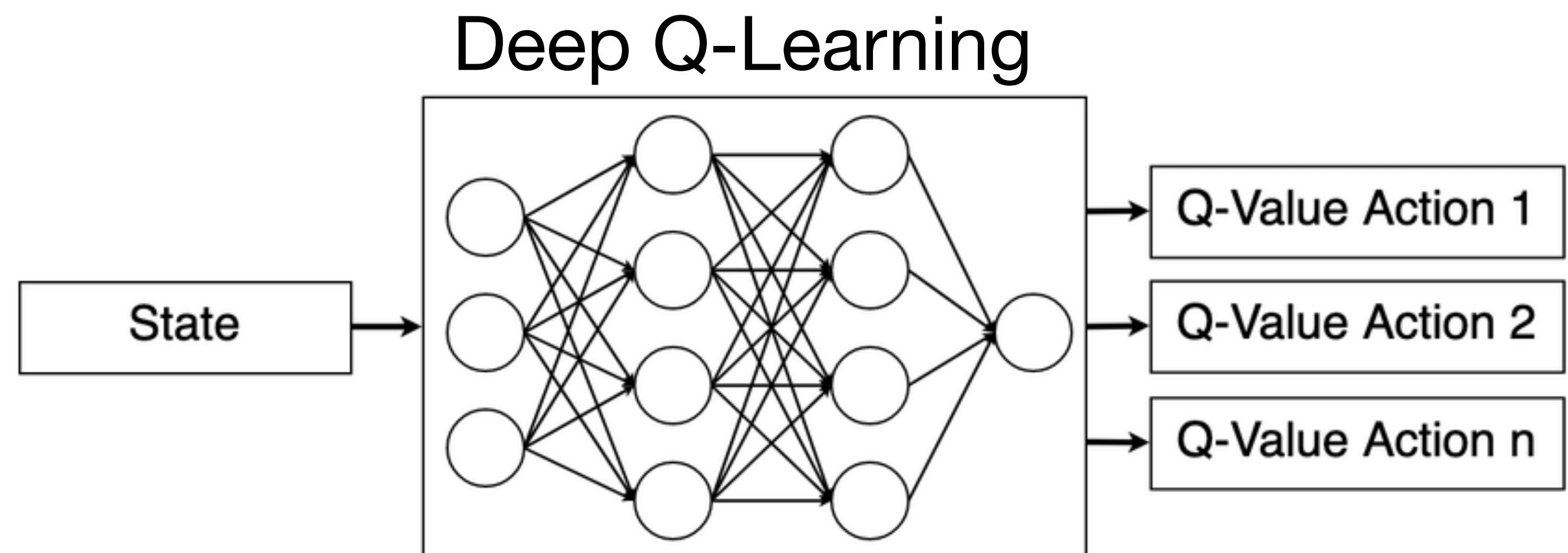
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Function approximation:

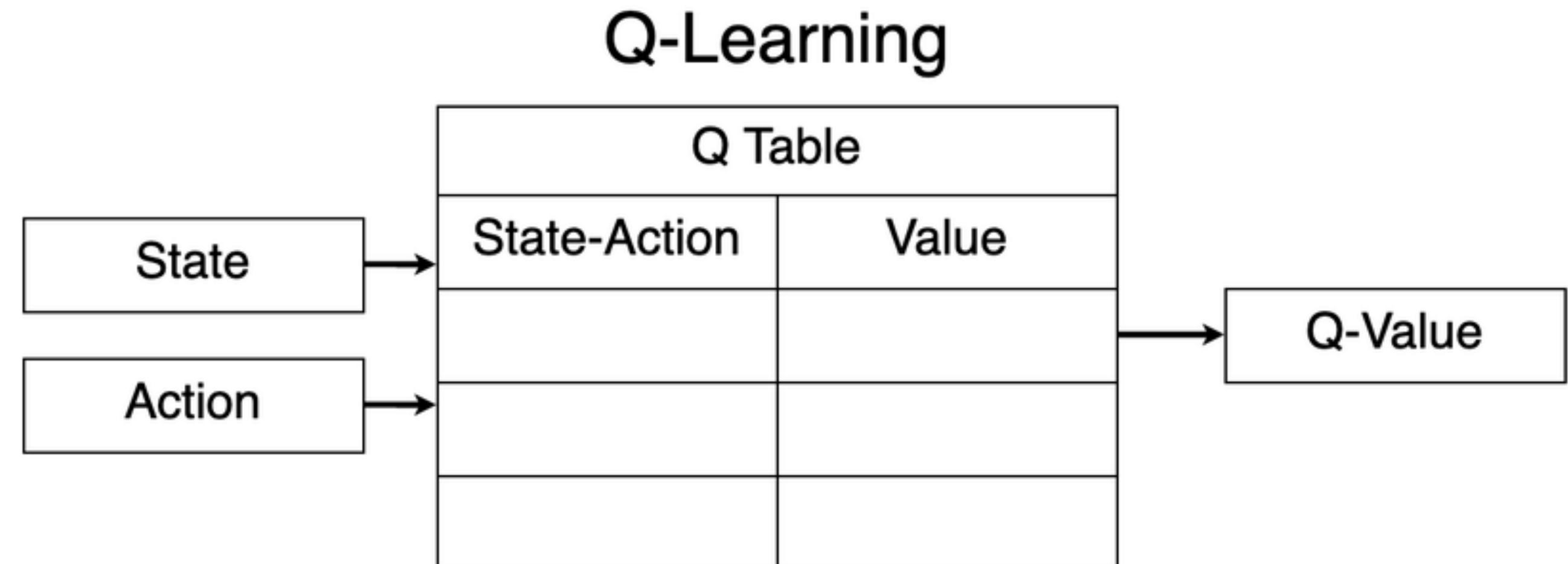
- Deep Q-Learning: use a deep ANN to learn $Q_{\mathbf{w}}(s, a)$



Deep Q-learning

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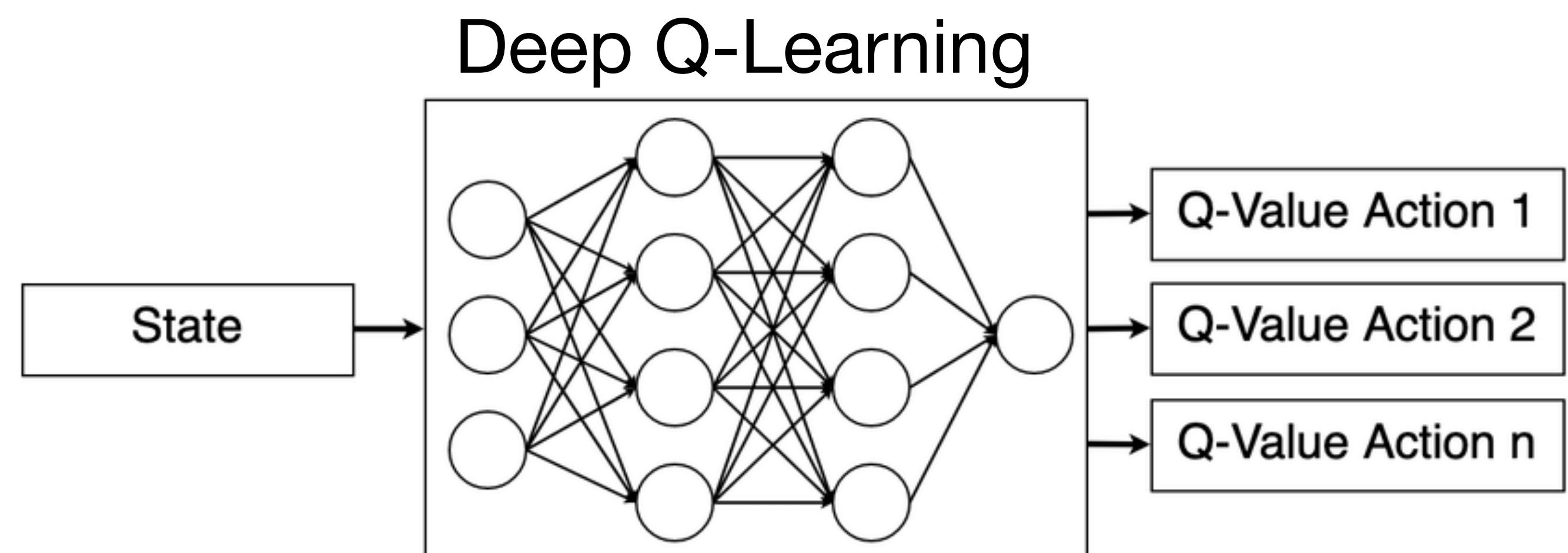
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Function approximation:

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- Weight updates:

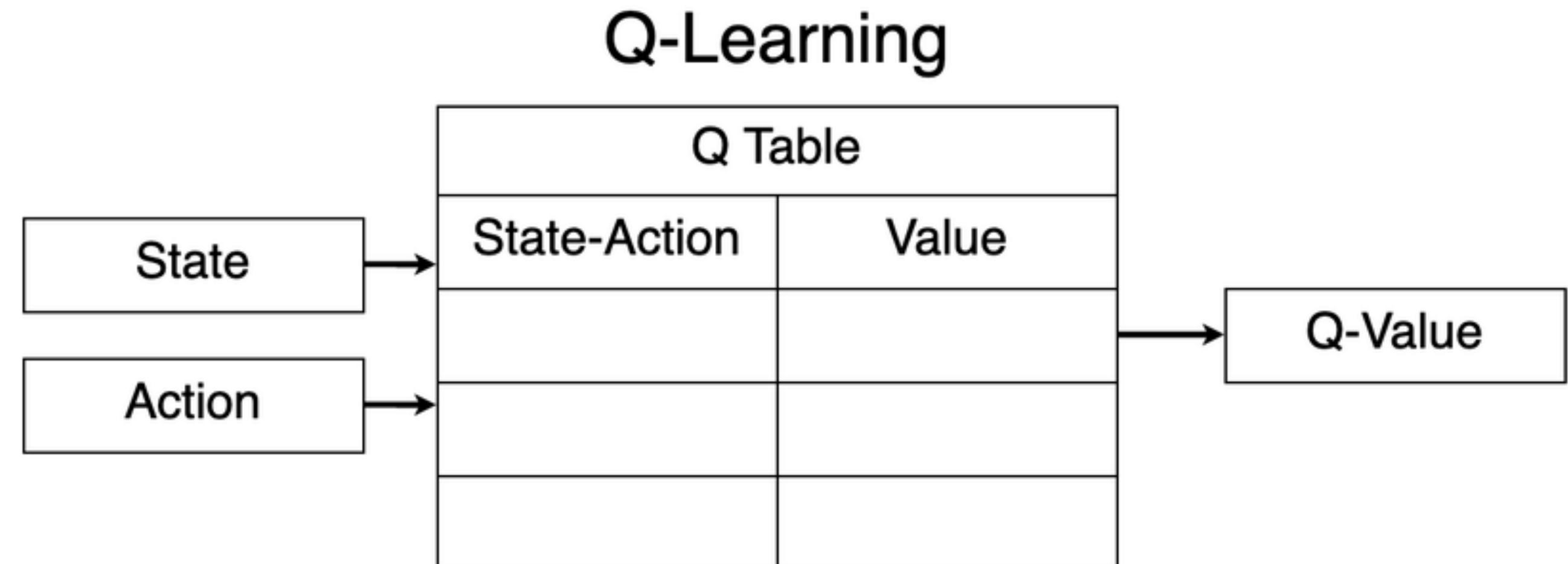
$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + \alpha \delta \nabla_{\mathbf{w}} Q_{\mathbf{w}}(s, a)$$



Deep Q-learning

Tabular methods:

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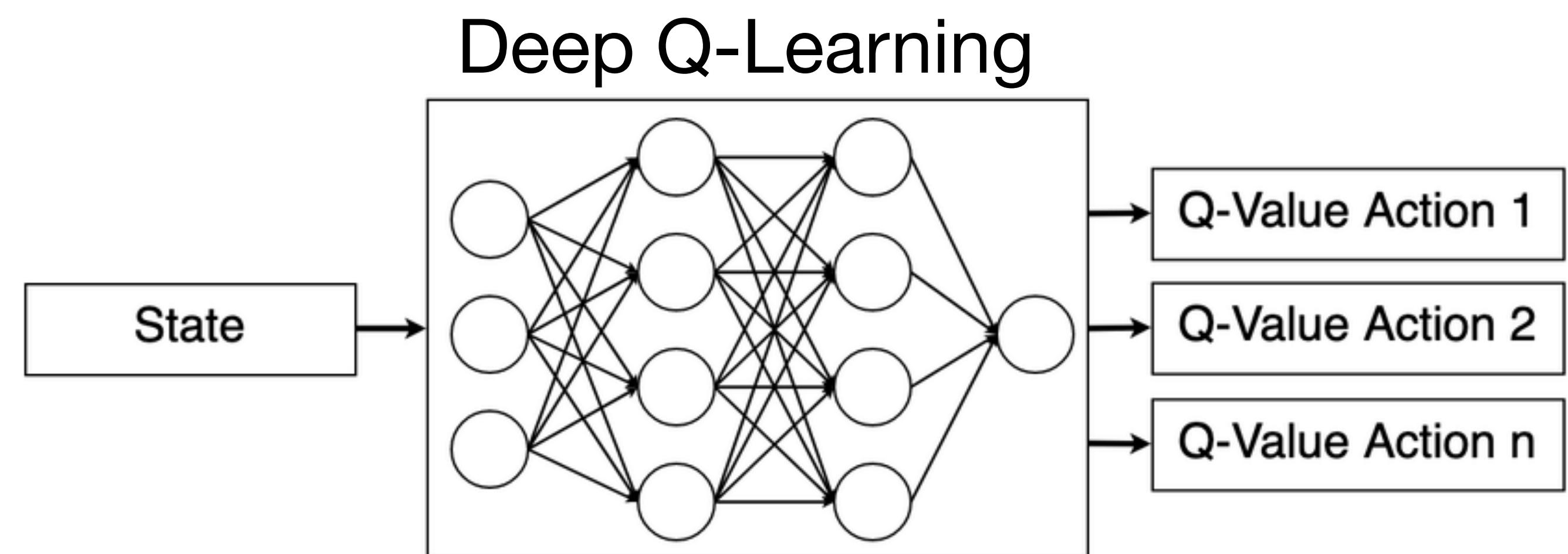
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- Weight updates: learning rate

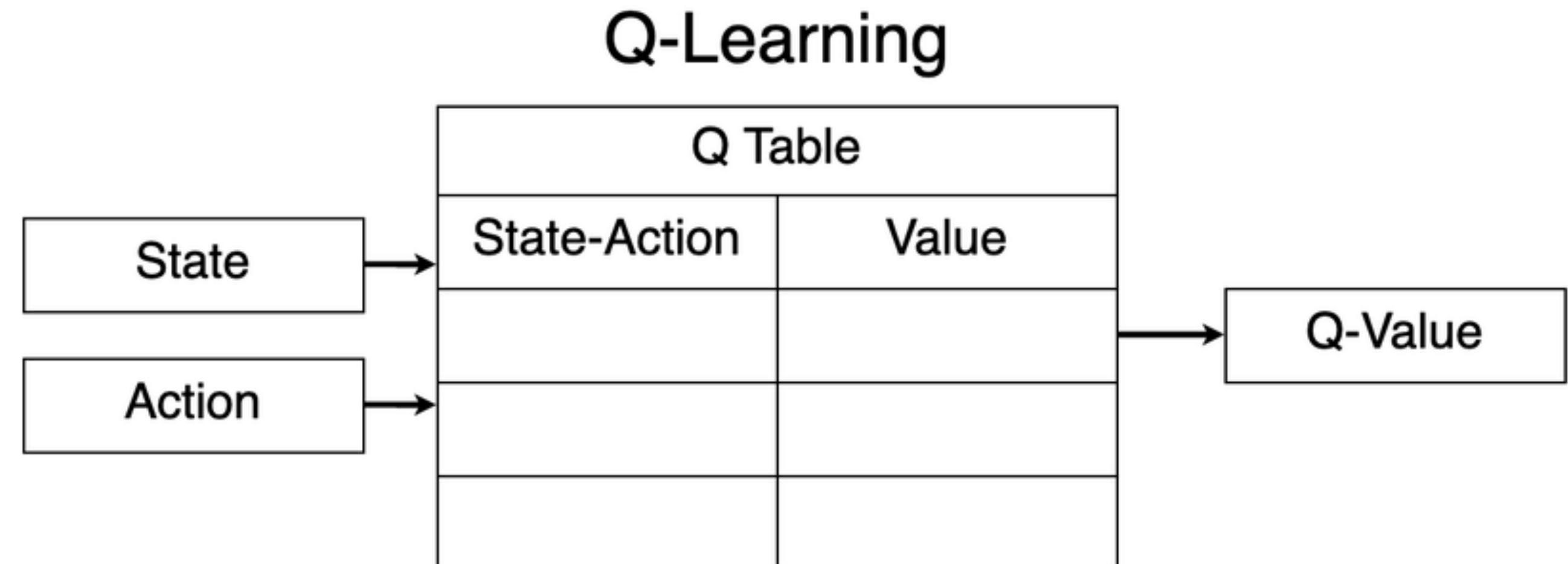
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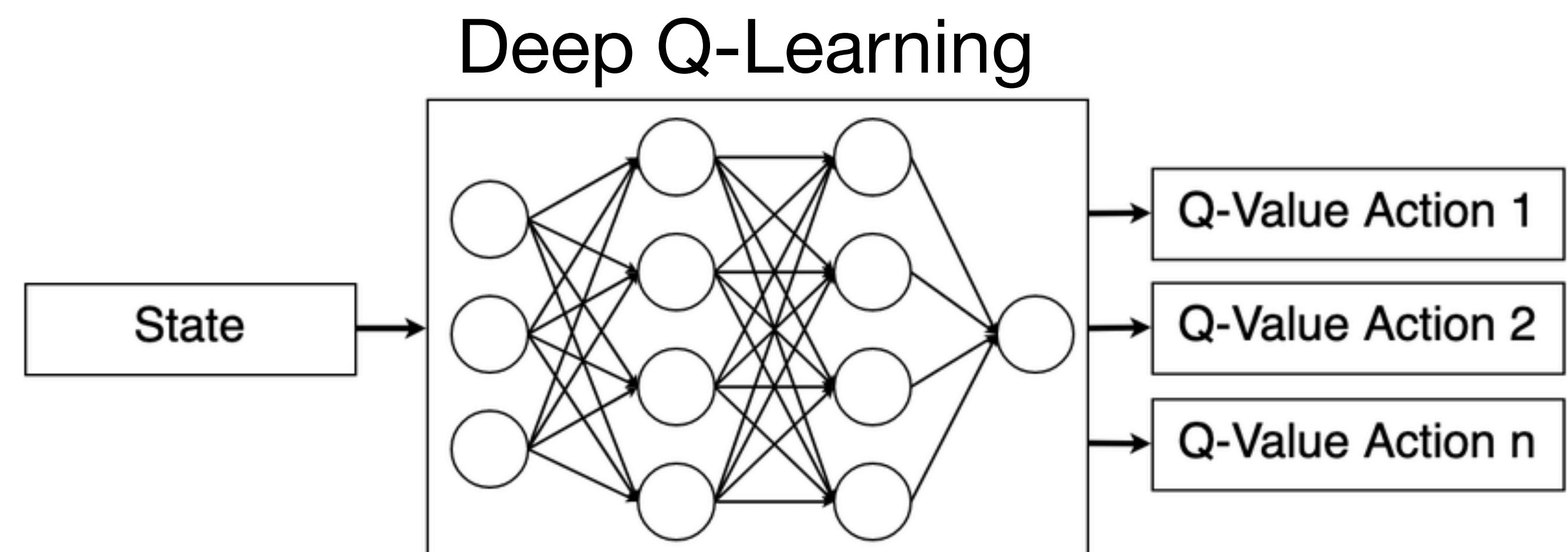
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- **TD prediction error**

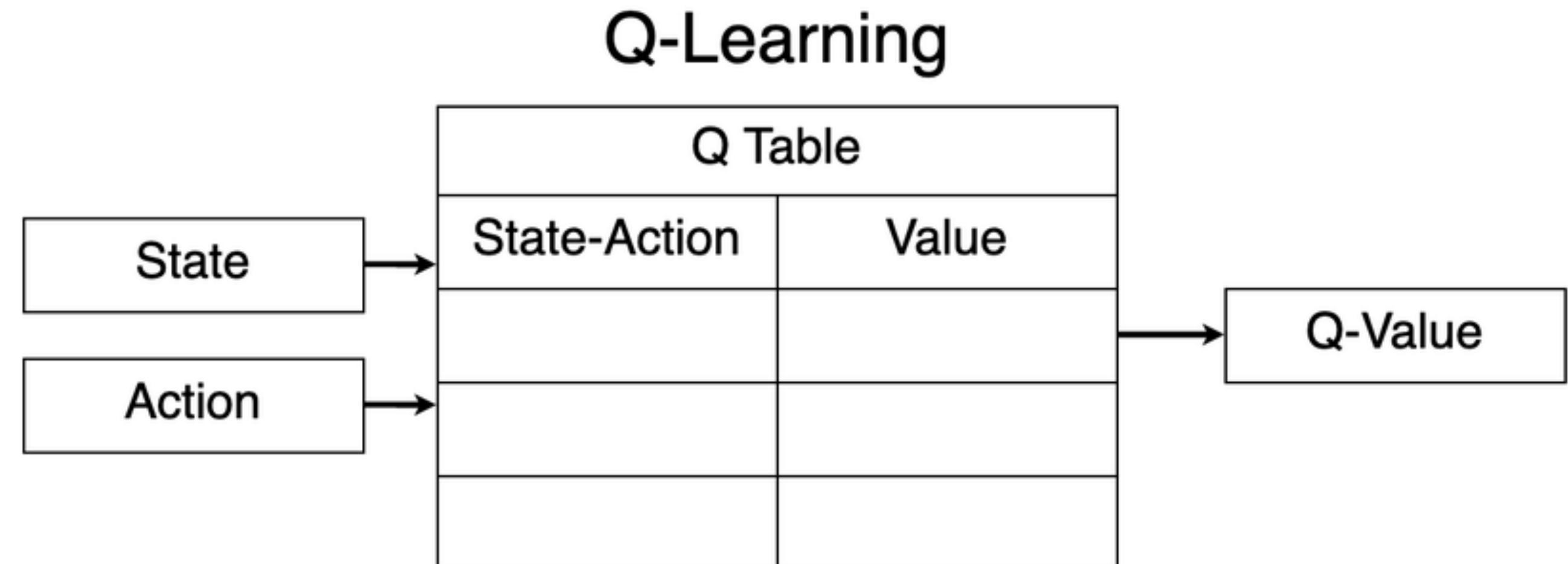
$$\delta = r + \gamma \max_{a'} Q_{\mathbf{w}}(s', a') - Q_{\mathbf{w}}(s, a)$$



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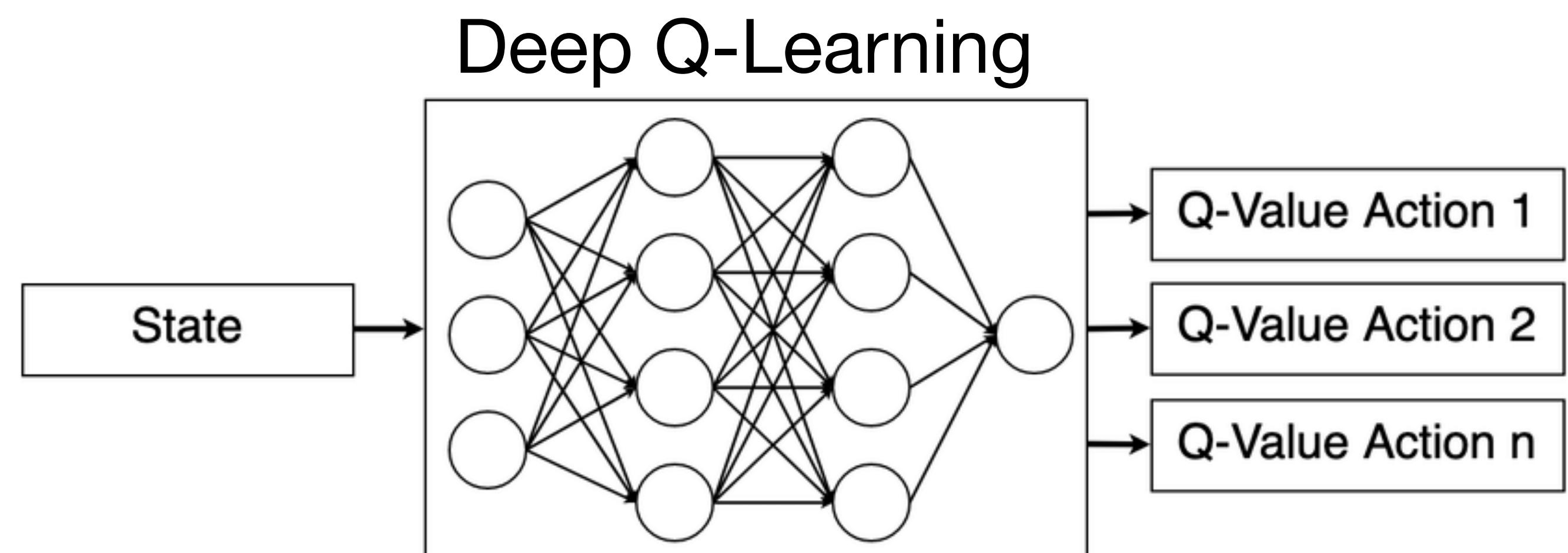
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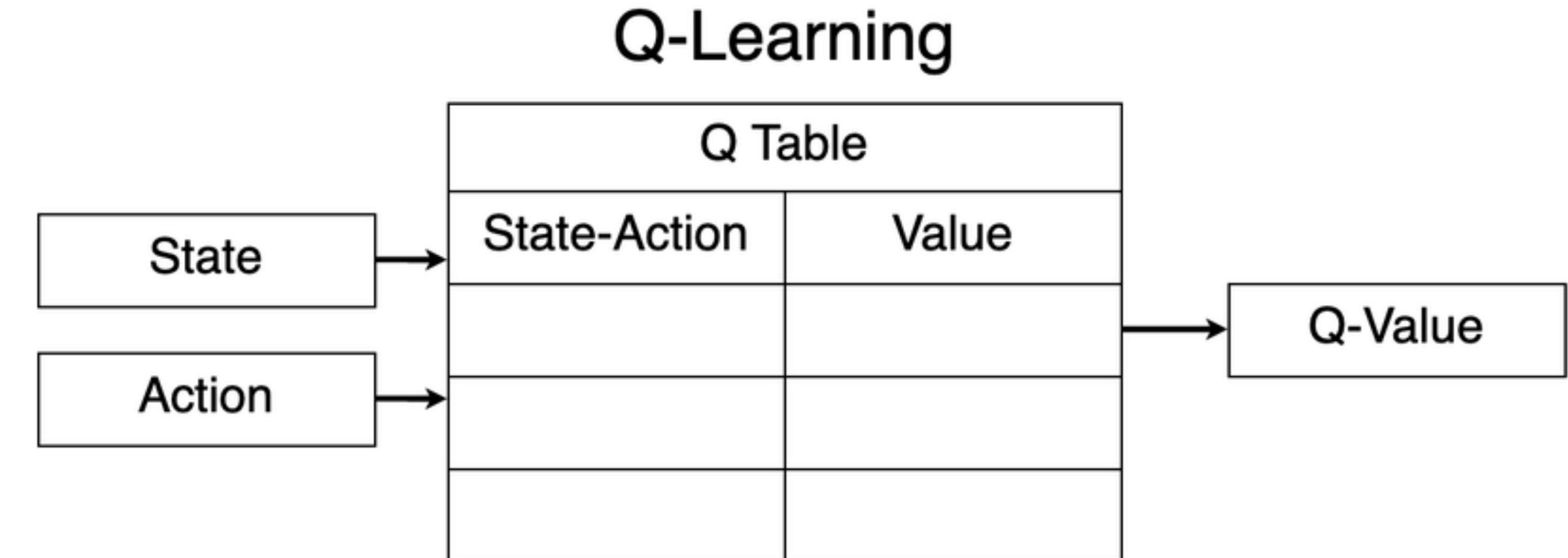
- **Gradient** of Q-function w.r.t. to \mathbf{w} , trying to reduce prediction error!



Deep Q-learning

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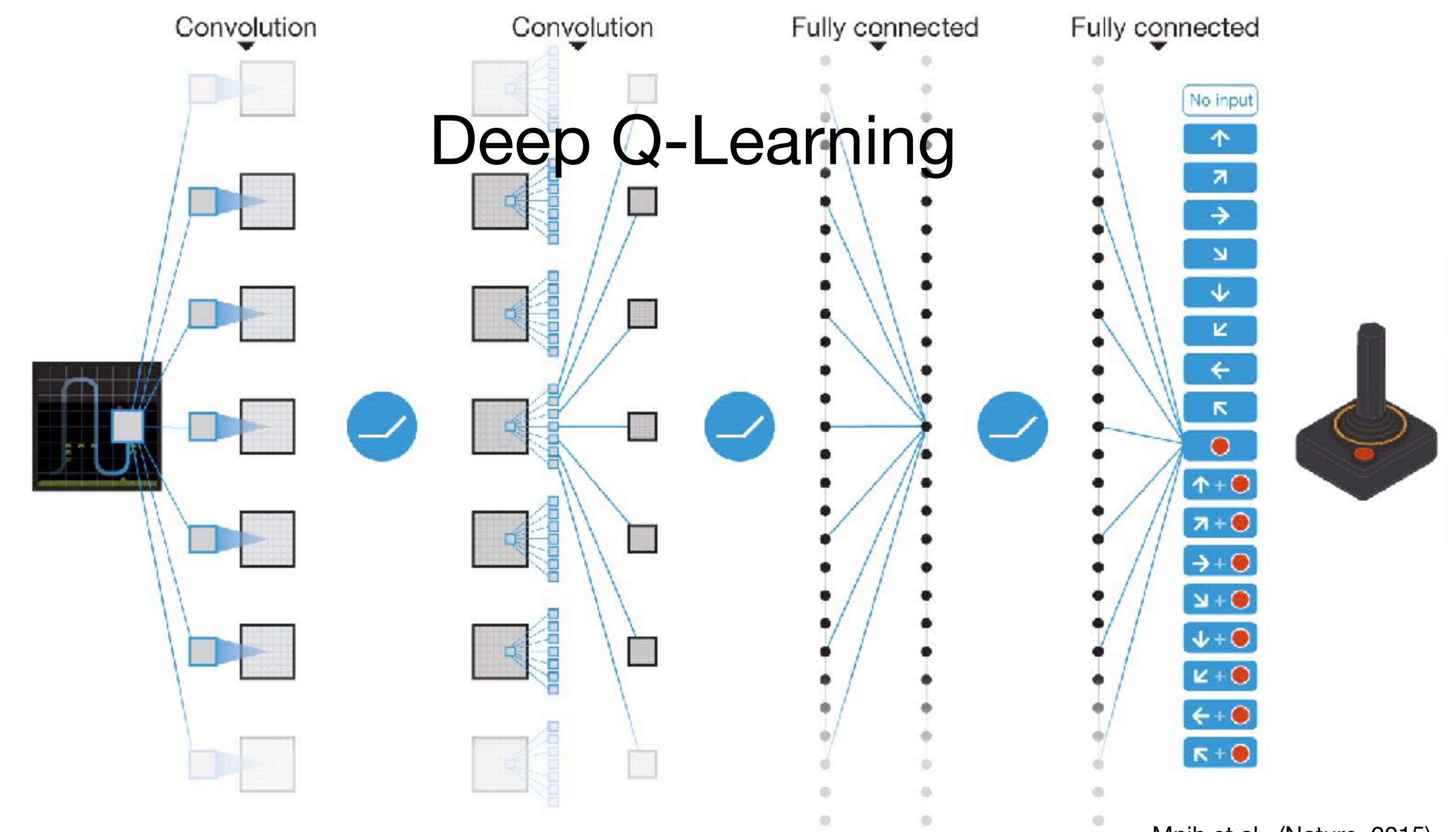
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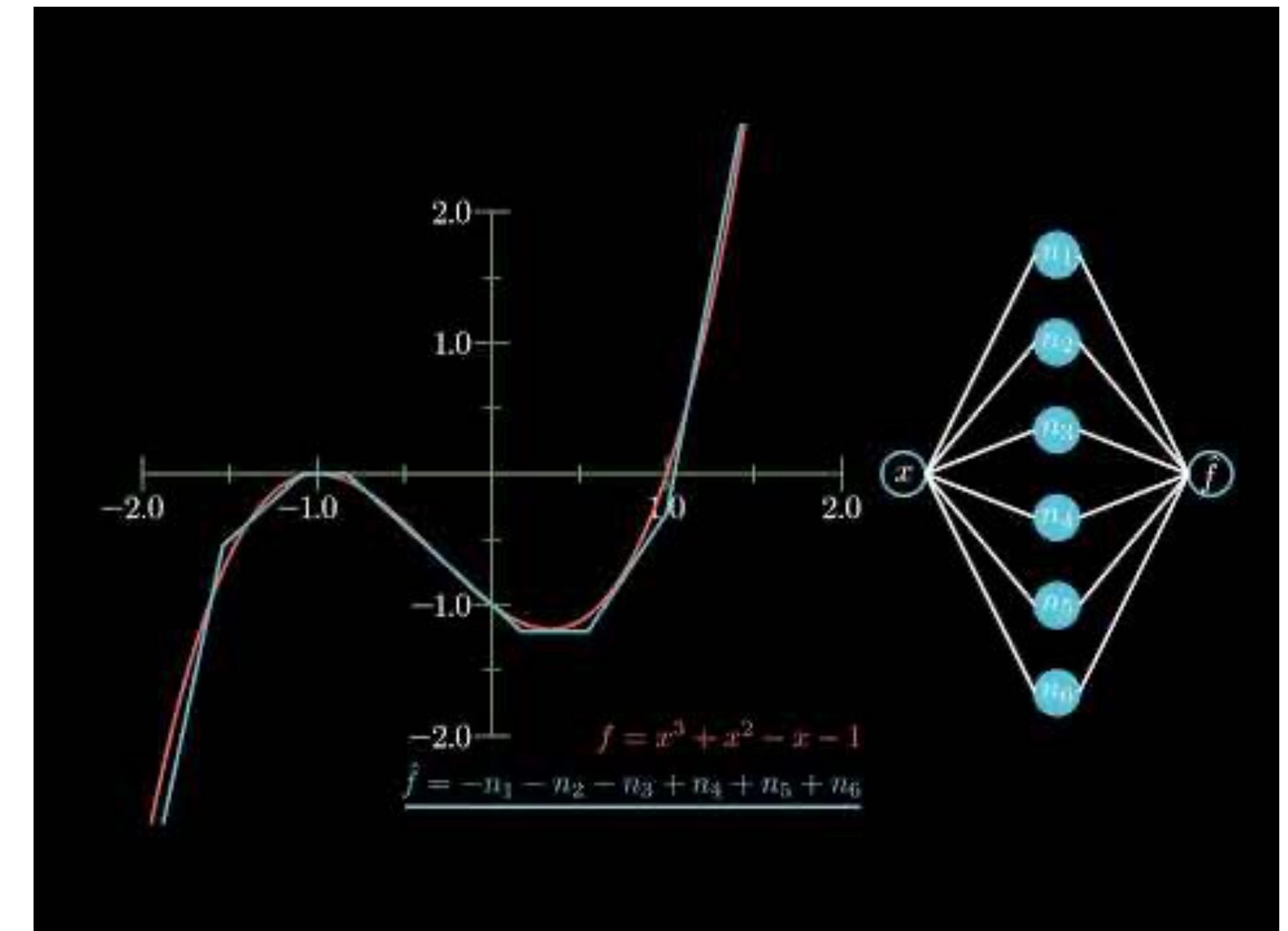
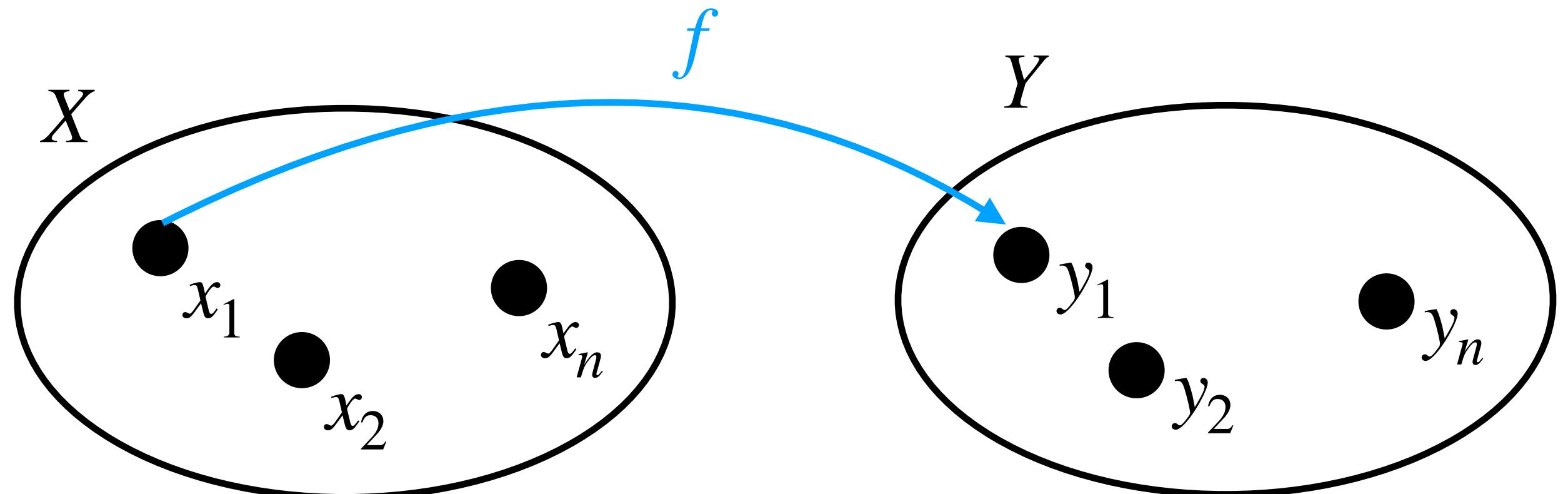
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Universal Approximation Theorem

Cybenko (1989)

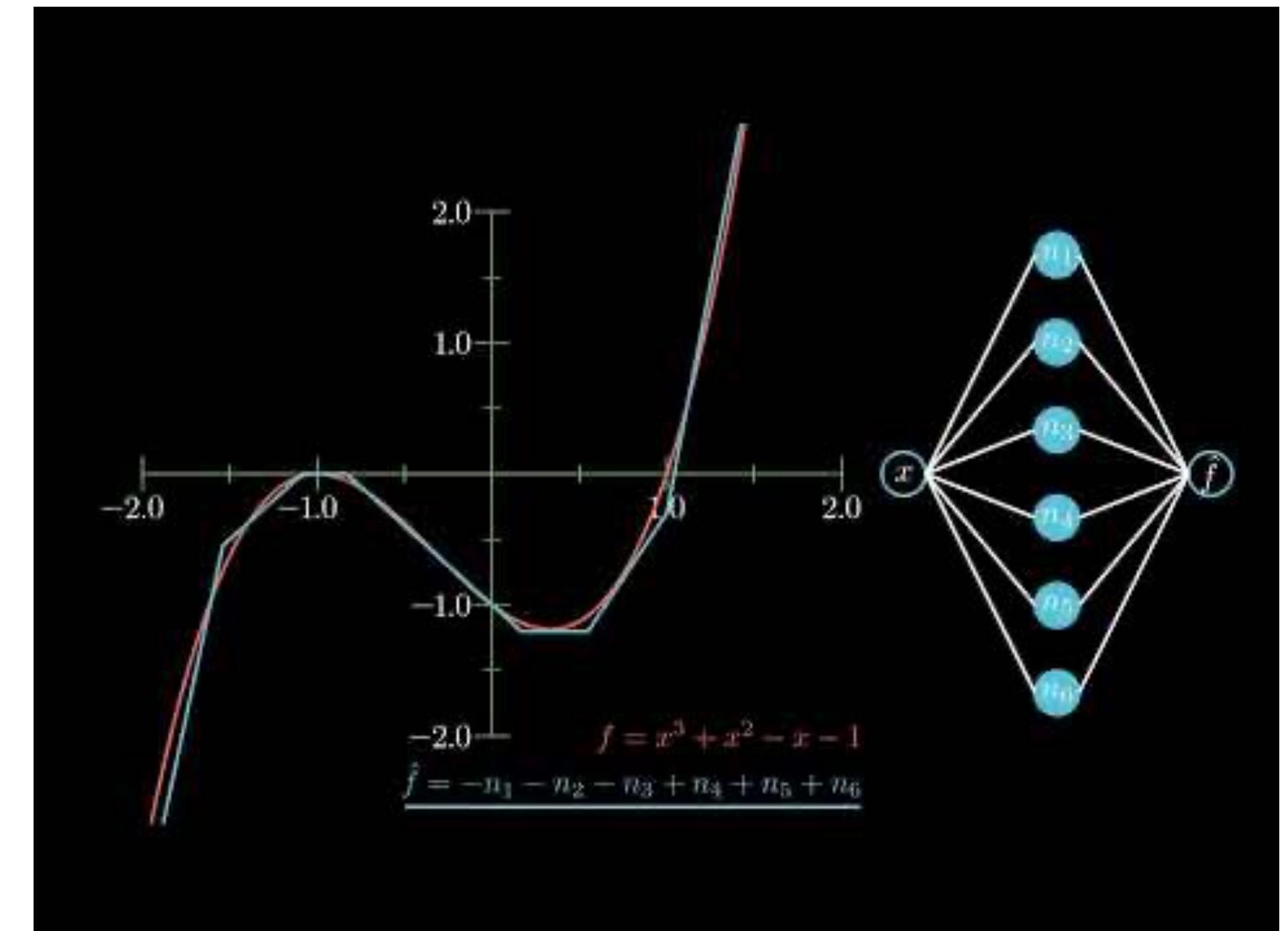
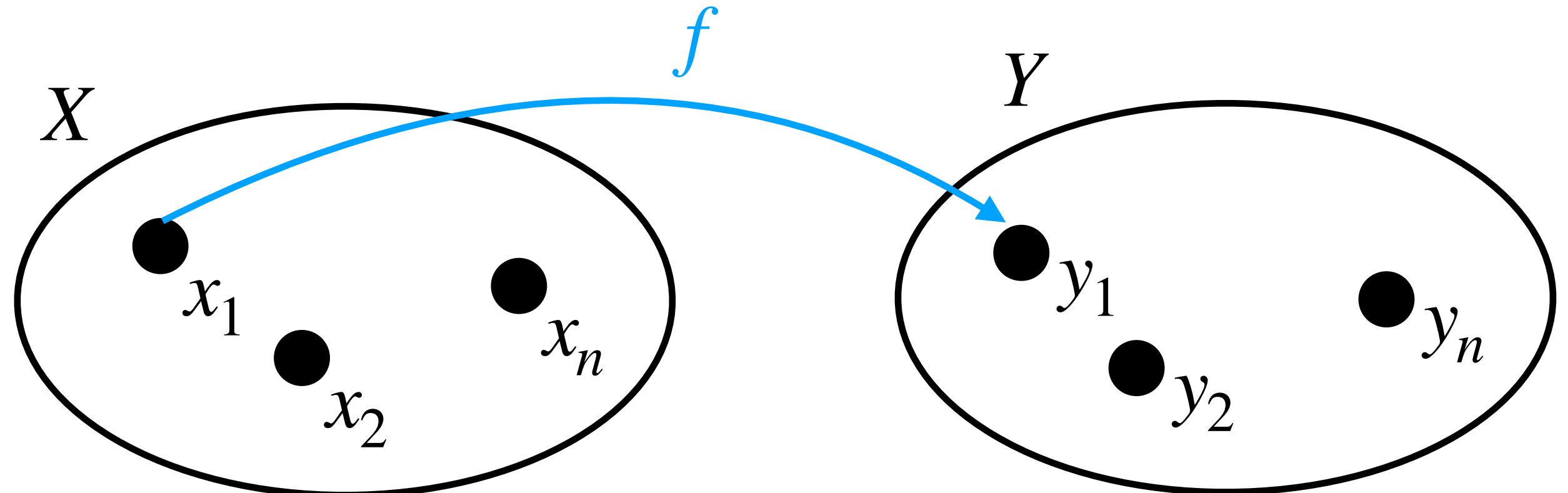
- What is a function?
 - $y = f(x)$
 - $f: X \rightarrow Y$
- ANNs are also functions
 - $g_{\mathbf{w}}(x) = \sigma(x)$ where \mathbf{w} are the connection weights
 - At least one neural network exists that can approximate any continuous function with arbitrary precision
 - $|g_{\mathbf{w}}(x) - f(x)| < \epsilon$



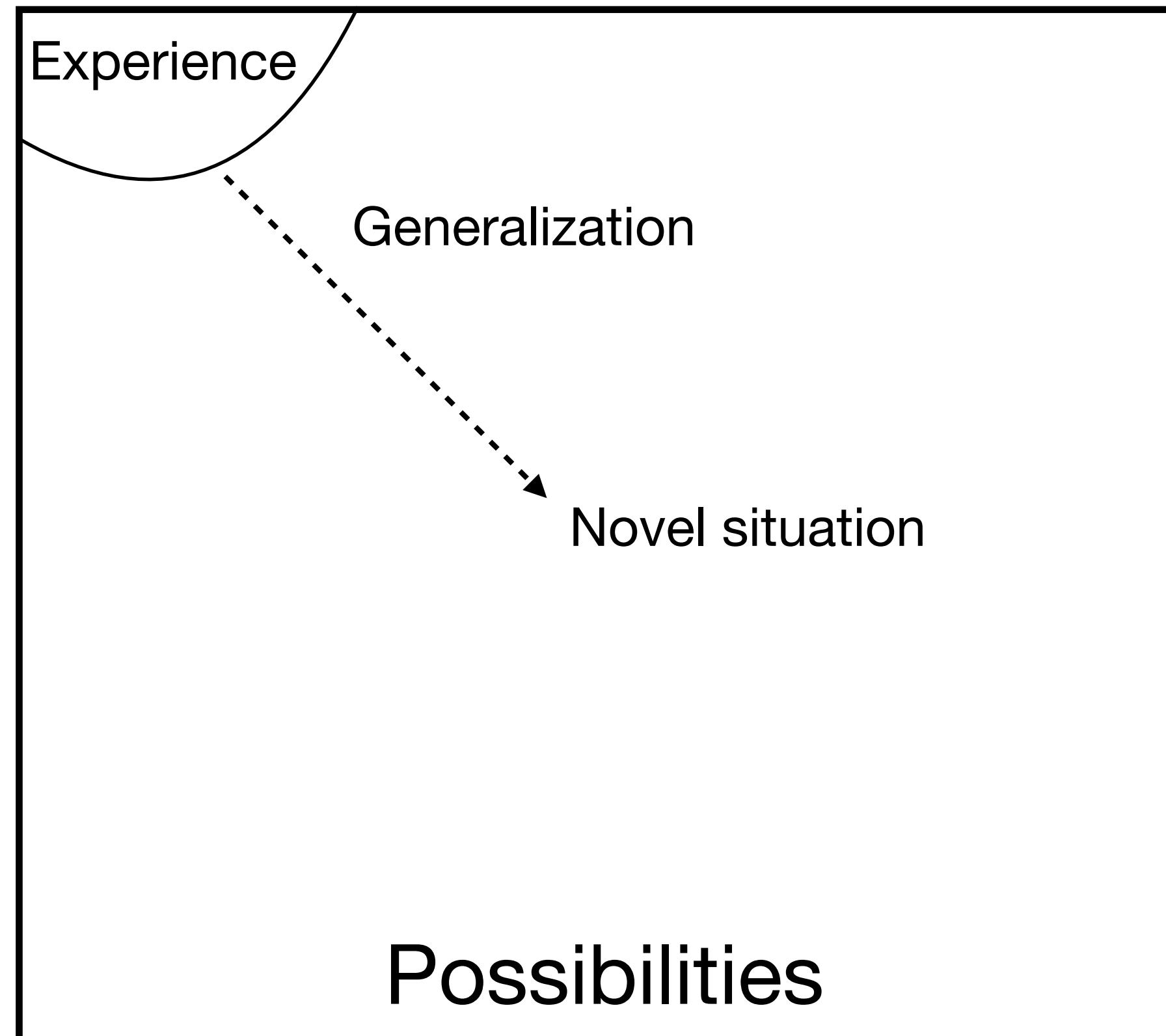
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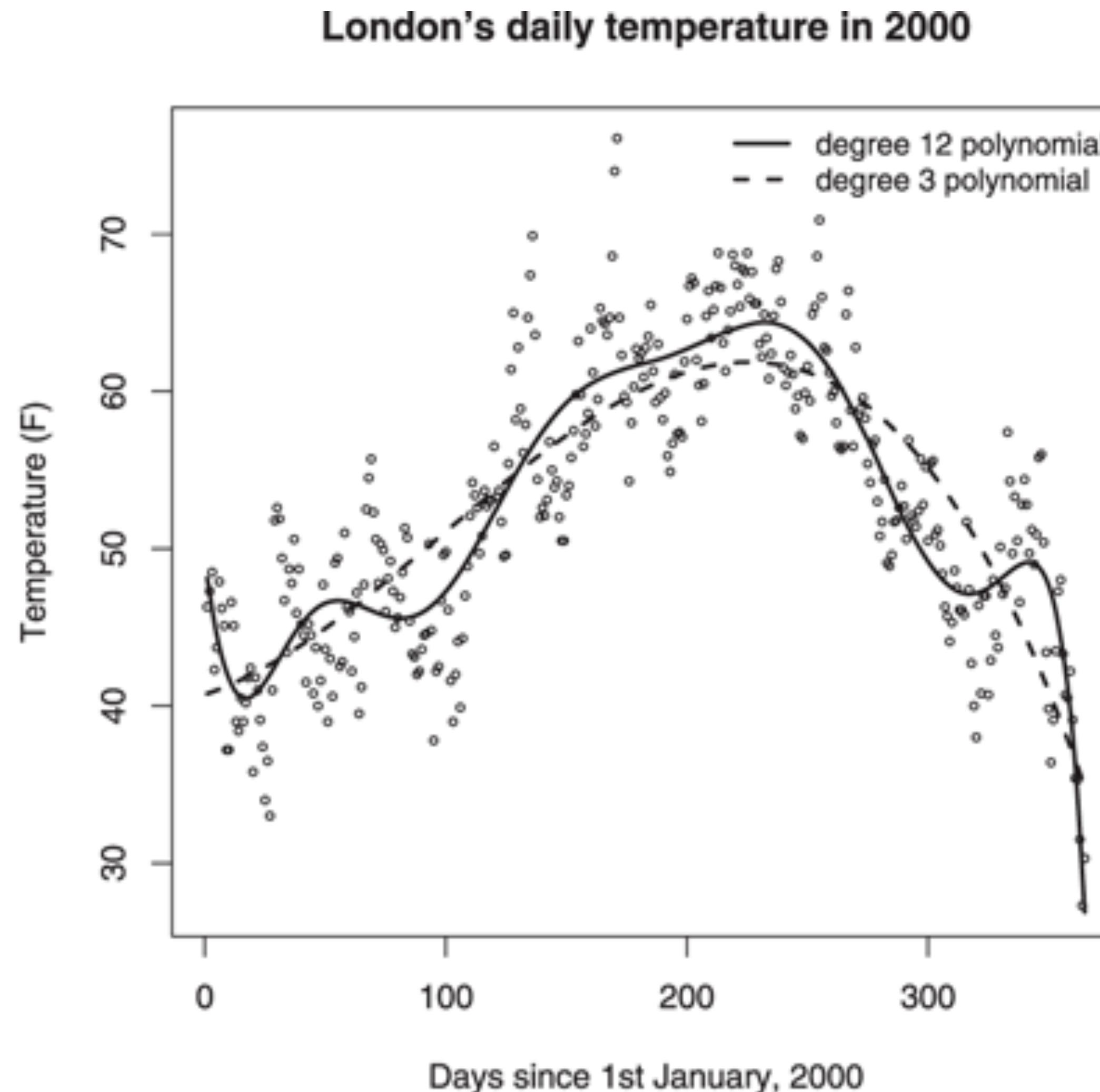
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Caveat: Approximation does not guarantee generalization

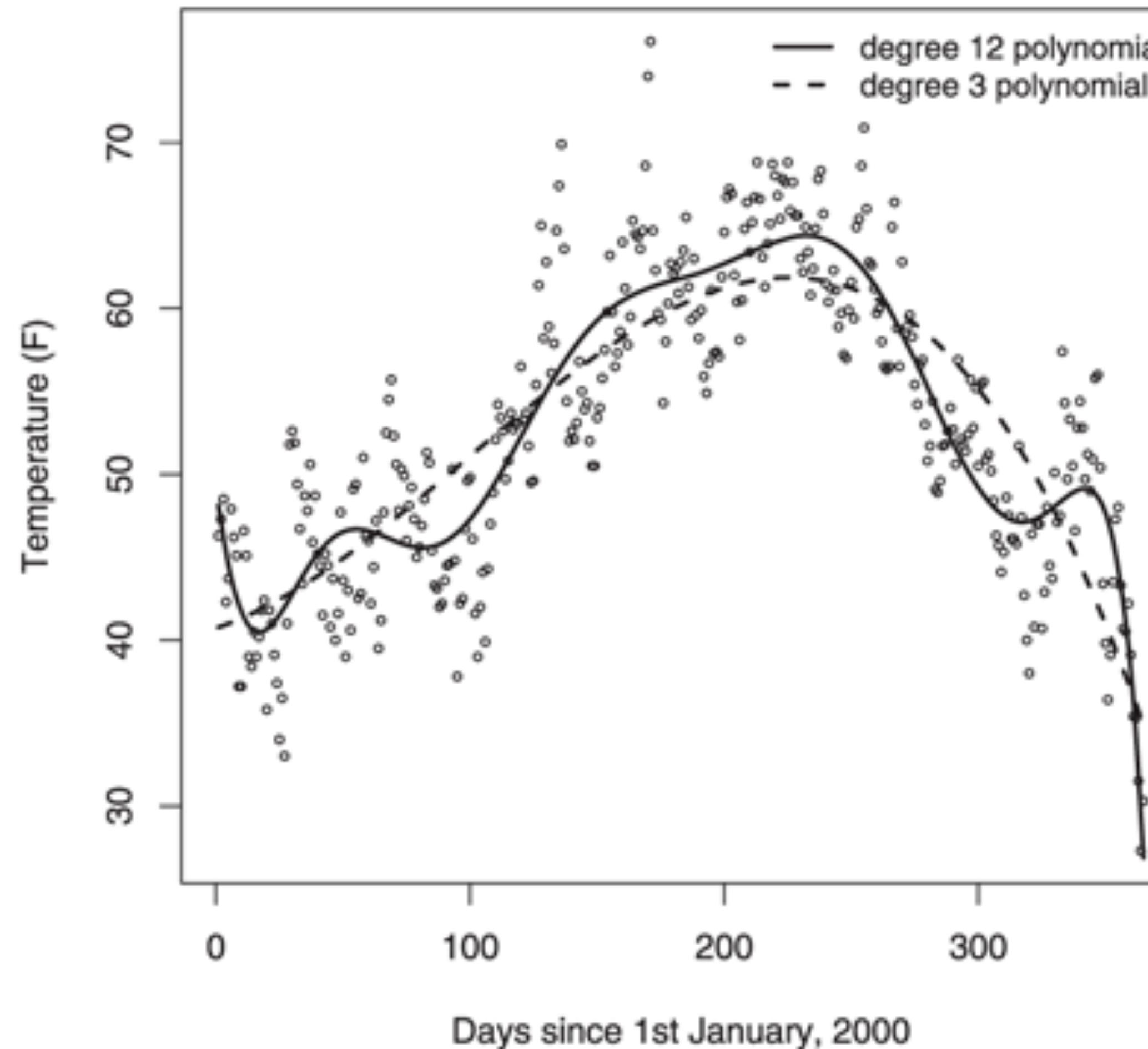


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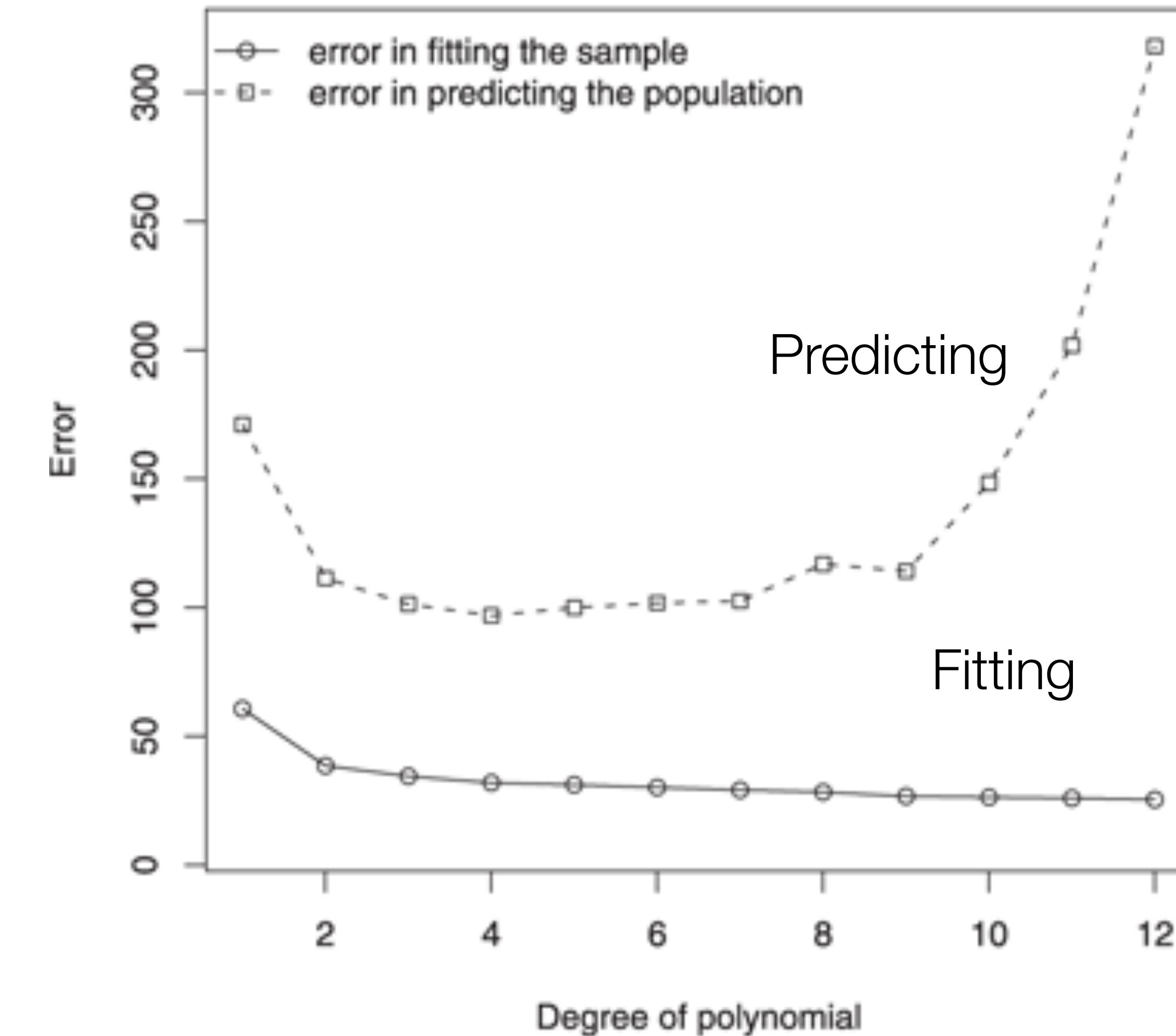


Caveat: Approximation does not guarantee generalization

London's daily temperature in 2000



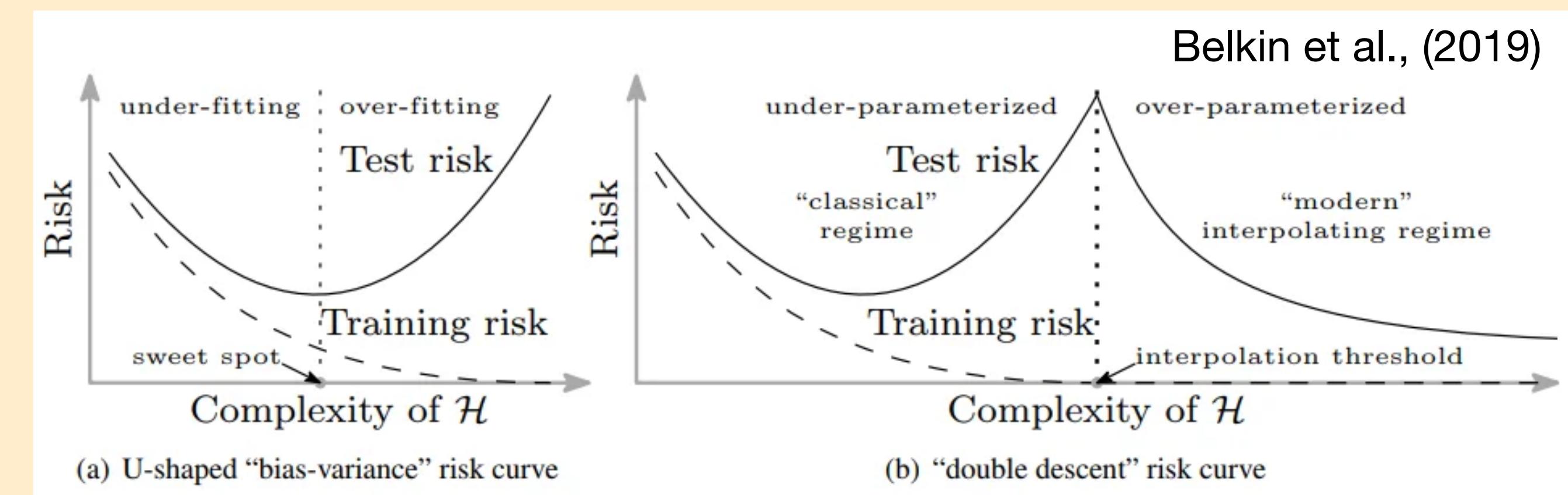
Model performance for London 2000 temperatures



Yet why do large ANNs work so well?

Not on the exam but very cool

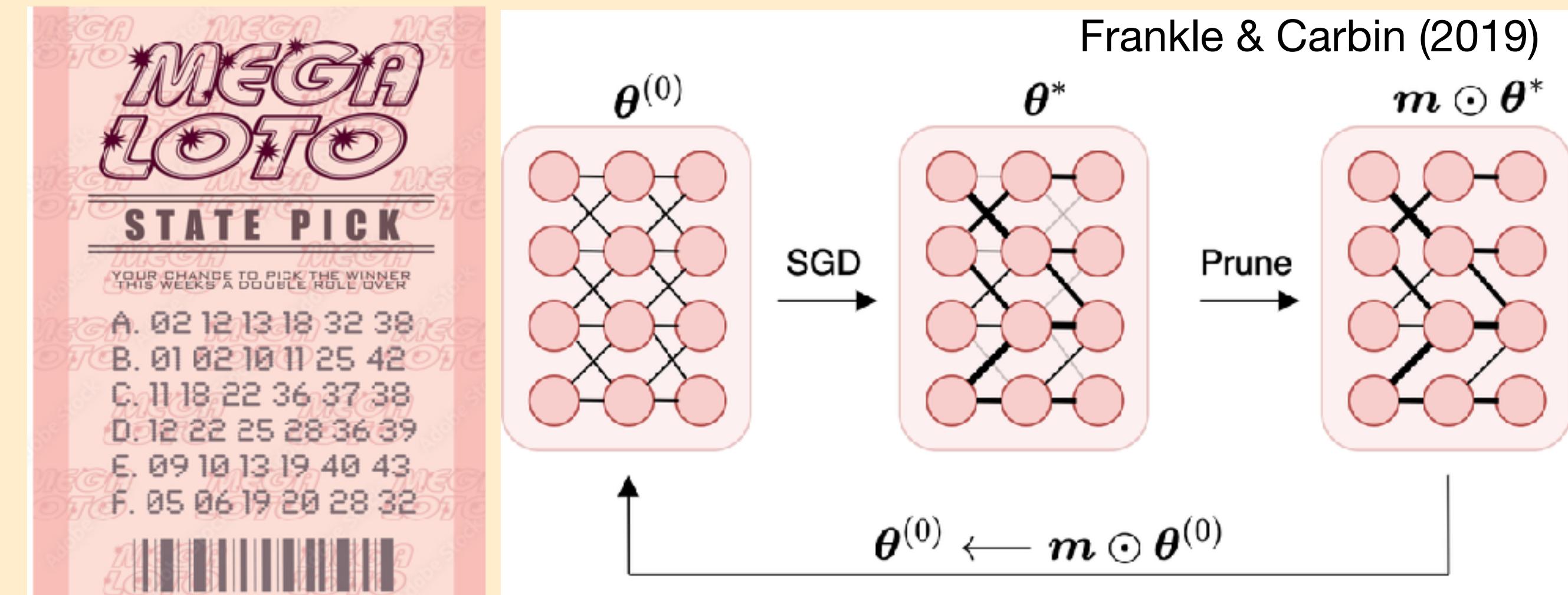
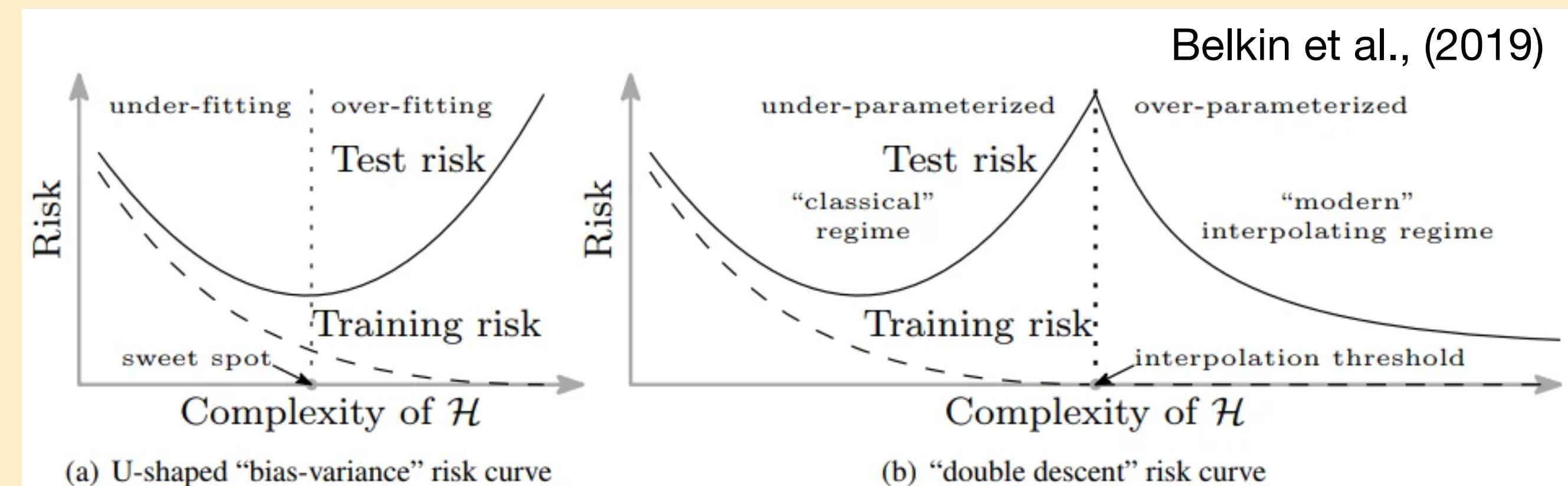
- Double descent phenomena
 - left: standard story
 - right: over-parameterized models start to reduce prediction error



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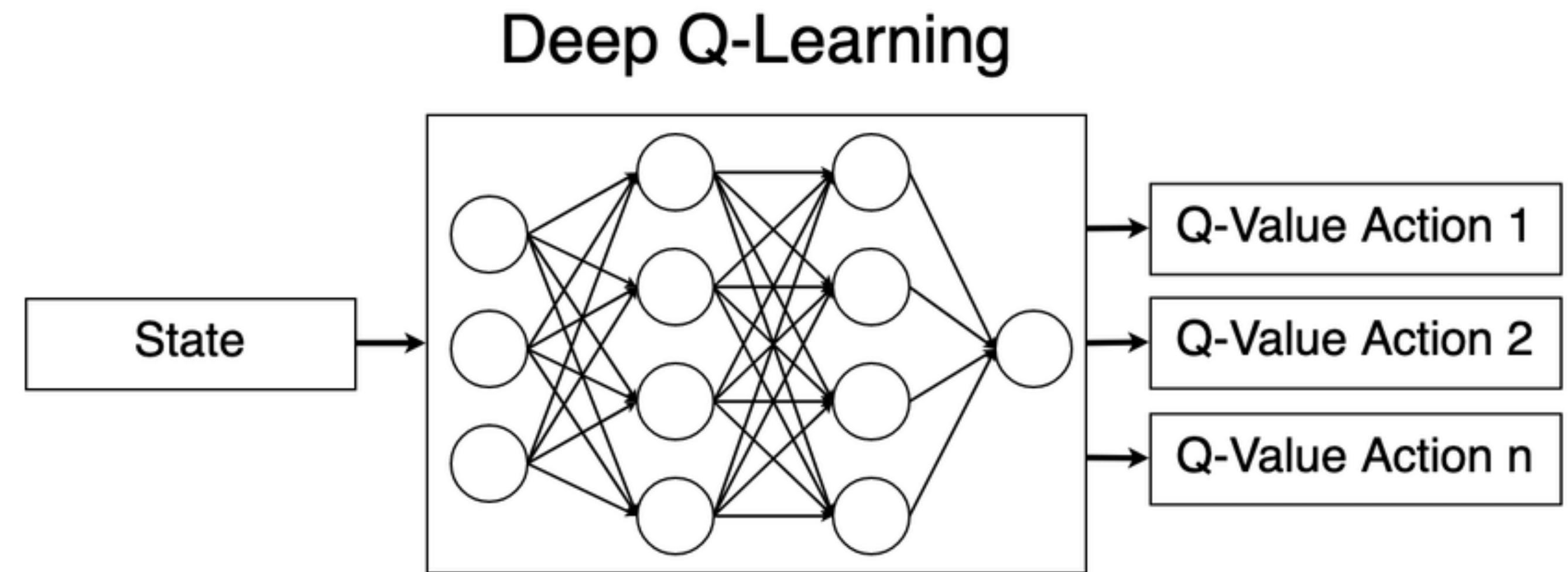
- Double descent phenomena
 - left: standard story
 - right: over-parameterized models start to reduce prediction error
- Lottery Ticket conjecture
 - *if you buy enough lottery tickets, one is bound to be a winner**
 - Large “over-parameterized” ANNs have a bunch of different **subnetworks** that are randomly initialized (i.e., lottery tickets)
 - SGD focuses on training winning subnetworks
 - Pruning connections not part of the winning ticket can improve efficiency and even performance
 - The effective complexity $\neq |\theta|$



*not actually good financial advice

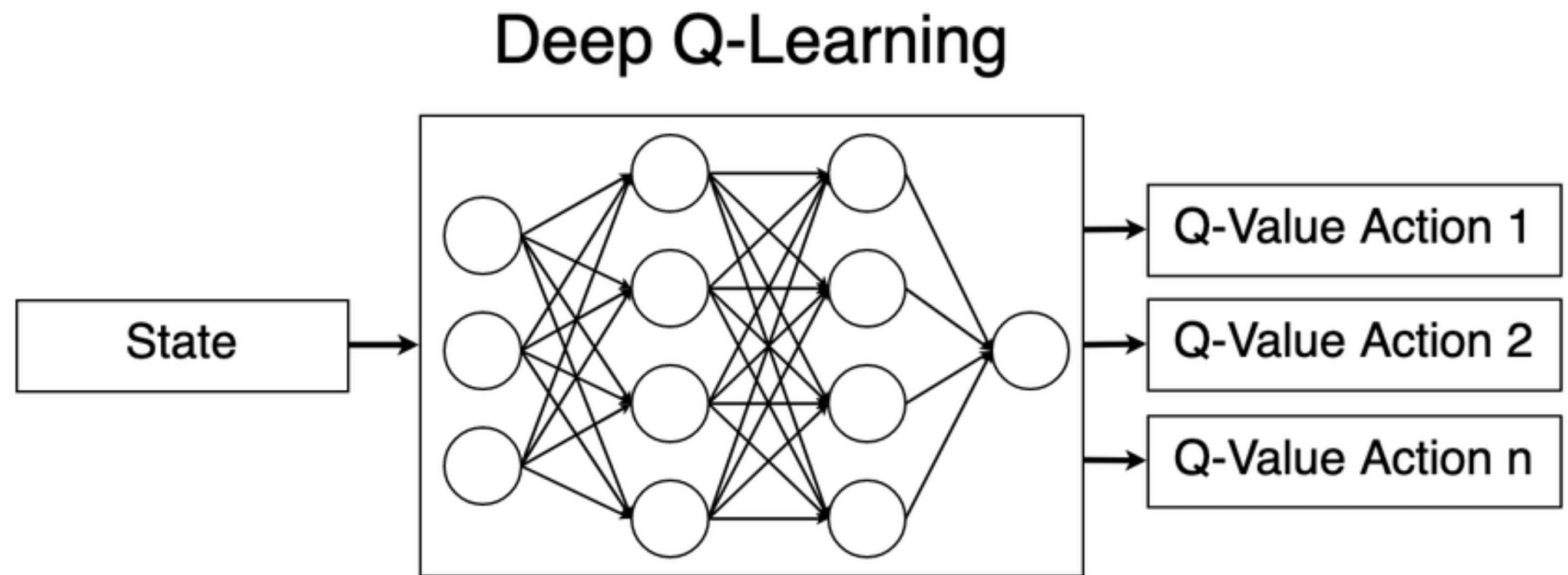
Policy Gradient

- **Deep Q-learning** uses an ANN to approximate the value function
 - the policy is implicit (e.g., a softmax over Q-values)



Policy Gradient

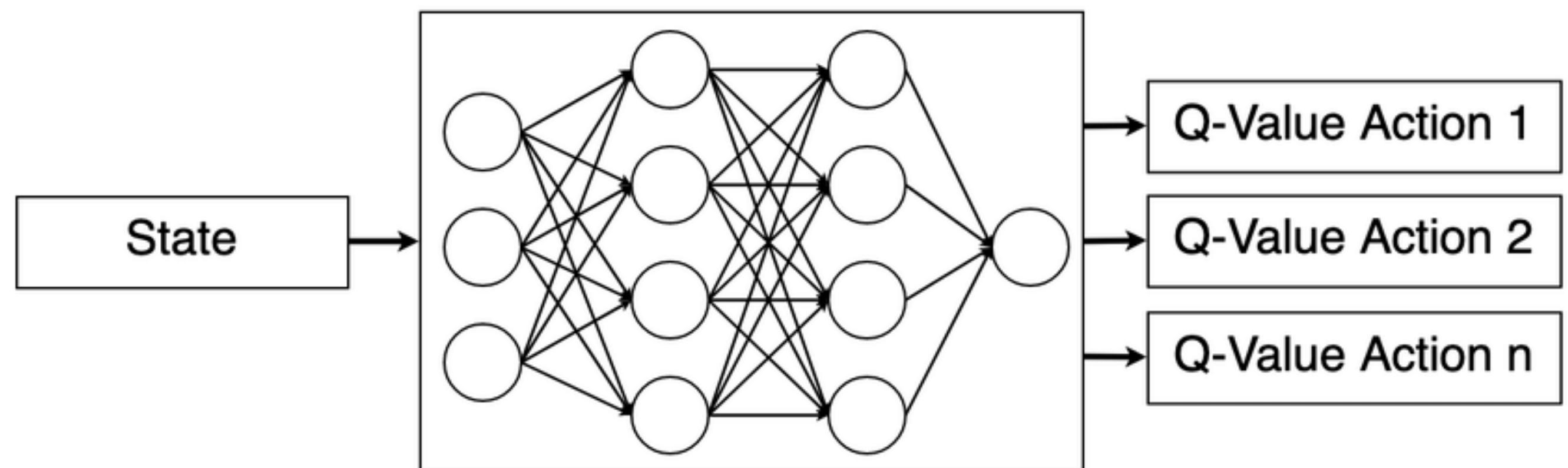
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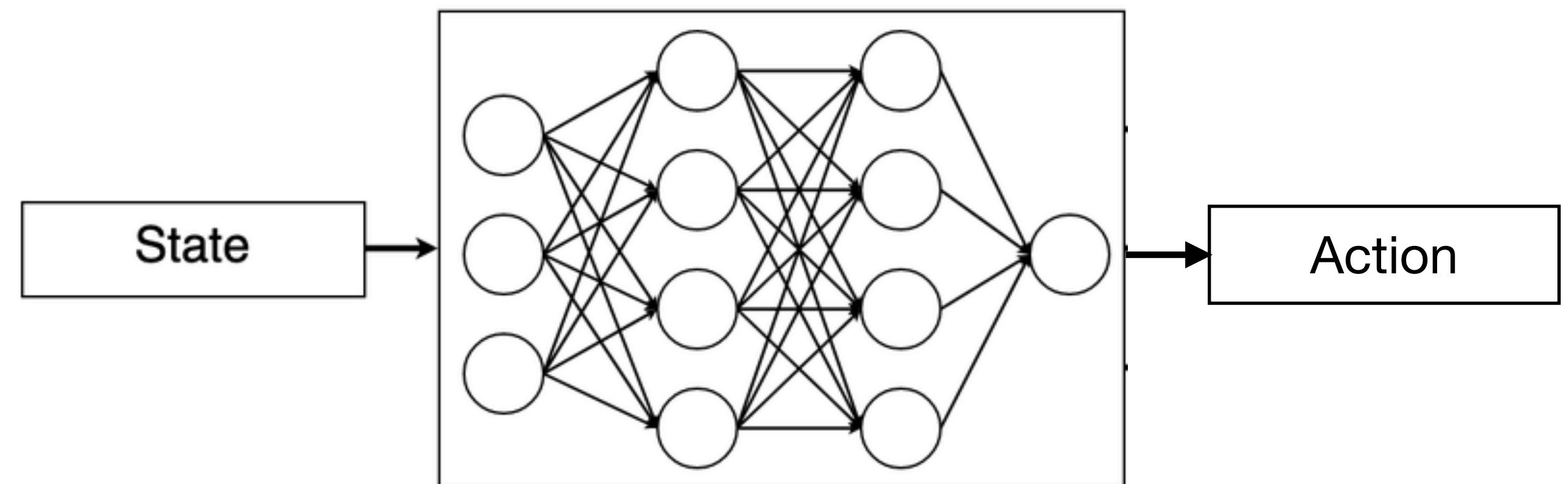
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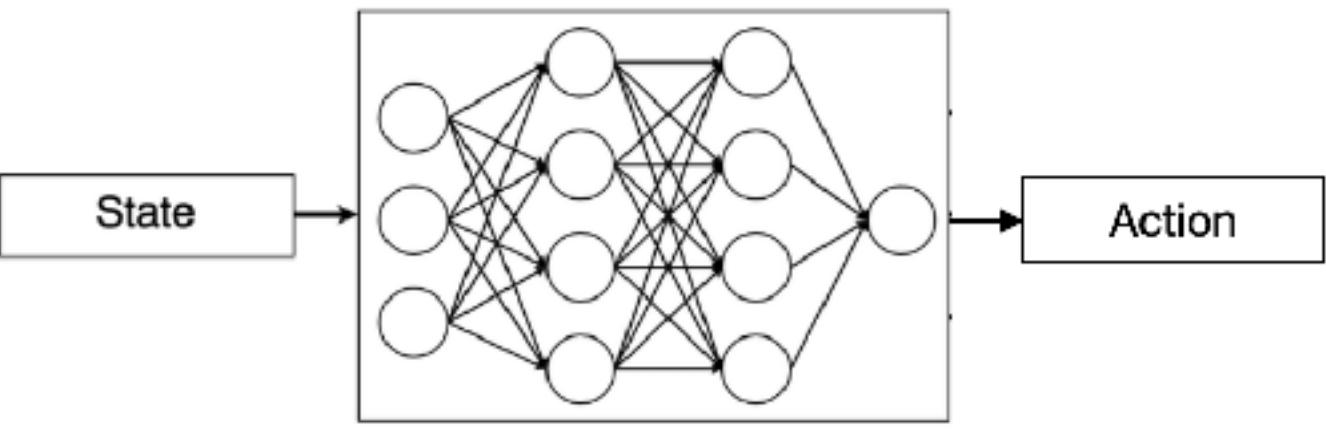
Deep Q-Learning



Policy Gradient



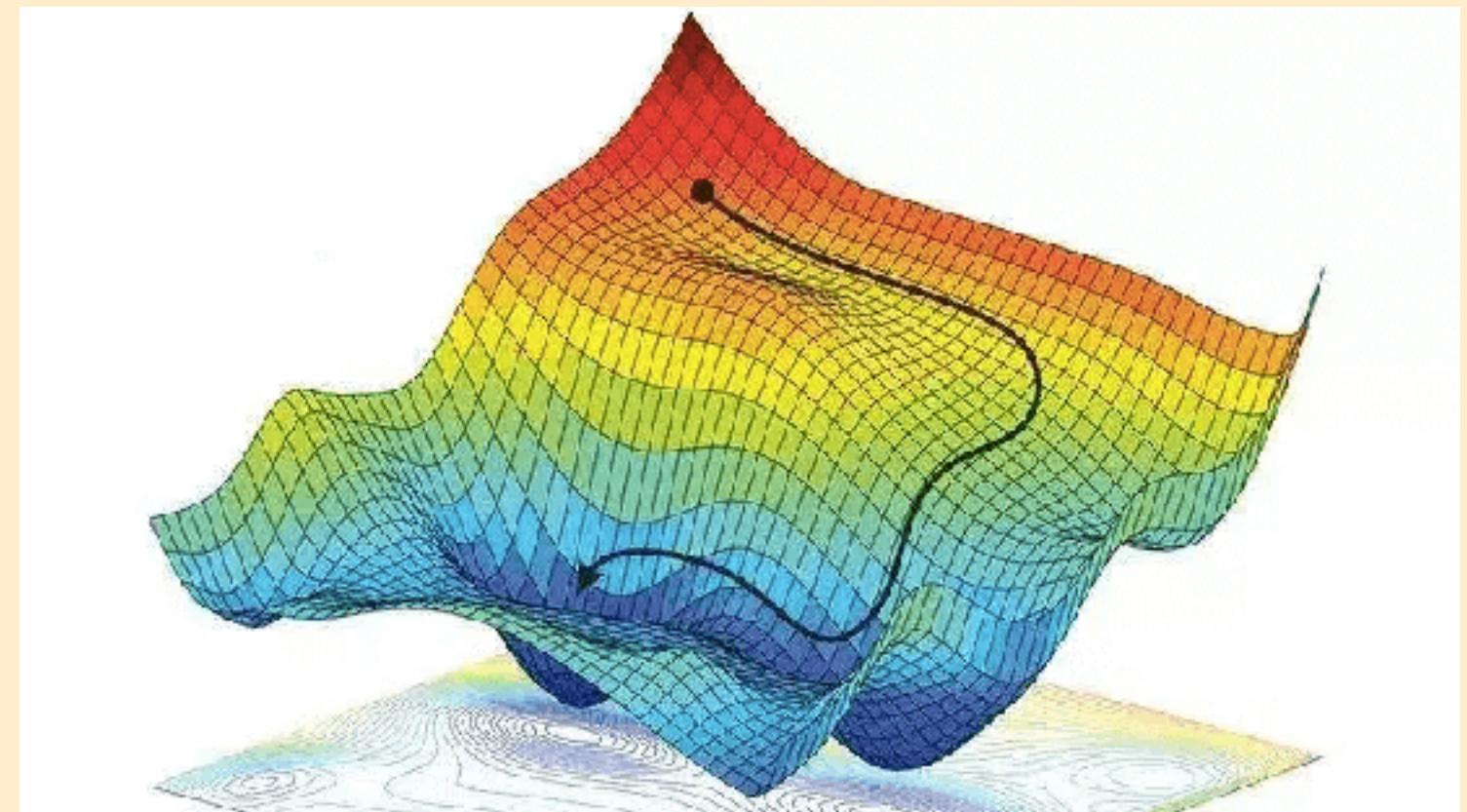
Policy Gradient



Formulas not on exam, but you should understand the general concept!

- Use a neural network to parameterize a policy $\pi_\theta(a | s)$
- Objective: Maximize expected reward following a parameterized policy: $J(\theta) = \mathbb{E}_{\tau \sim \pi_\theta}[r(\tau)]$
- Method: using gradient ascent $\theta_{t+1} = \theta_t + \beta \nabla_\theta J(\theta_t)$
learning rate
- Using the Markov principle, we can write the gradient as:

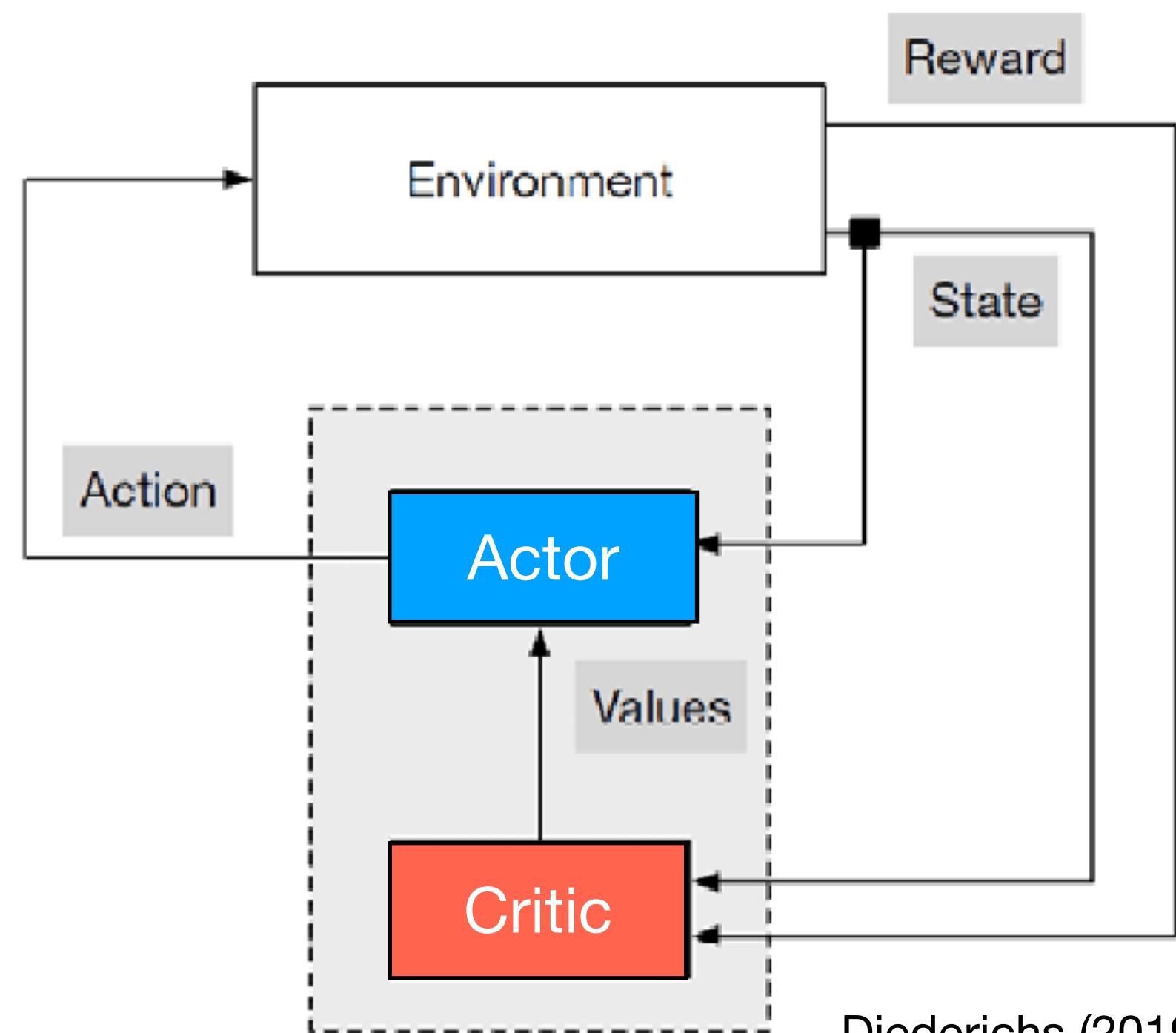
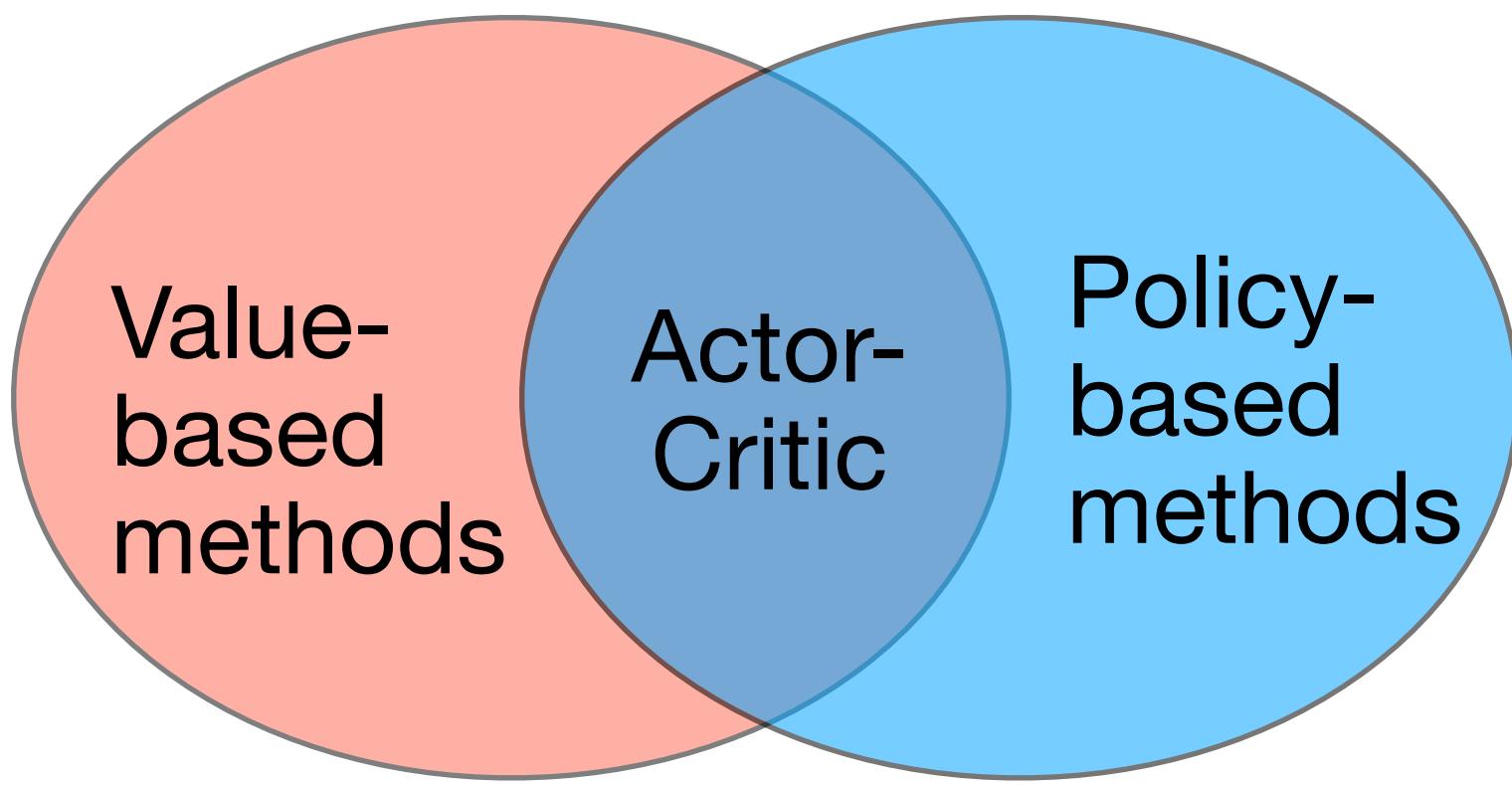
$$\nabla J(\theta_t) = \mathbb{E}_{\pi_\theta} \left[\sum_{t \in \tau}^{| \tau |} \nabla \log \pi_\theta(a_t | s_t) Q(a_t, s_t) \right]$$



- Updates to θ follow the **gradient** to increase the probability of highly rewarding actions:
$$\theta_{t+1} = \theta_t + \alpha \nabla_\theta \log \pi_\theta(a_t | s_t) Q(a_t, s_t)$$
- Here, $Q(a_t, s_t)$ is usually estimated through Monte Carlo sampling

Actor-Critic

- Actor-critic combines **value-based** and **policy-based** methods and is a generalization of policy iteration
 - **Actor** provides the policy $\pi_\theta(a | s)$ parameterized by θ
 - **Critic** provides the value function $Q_w(s, a)$ parameterized by w



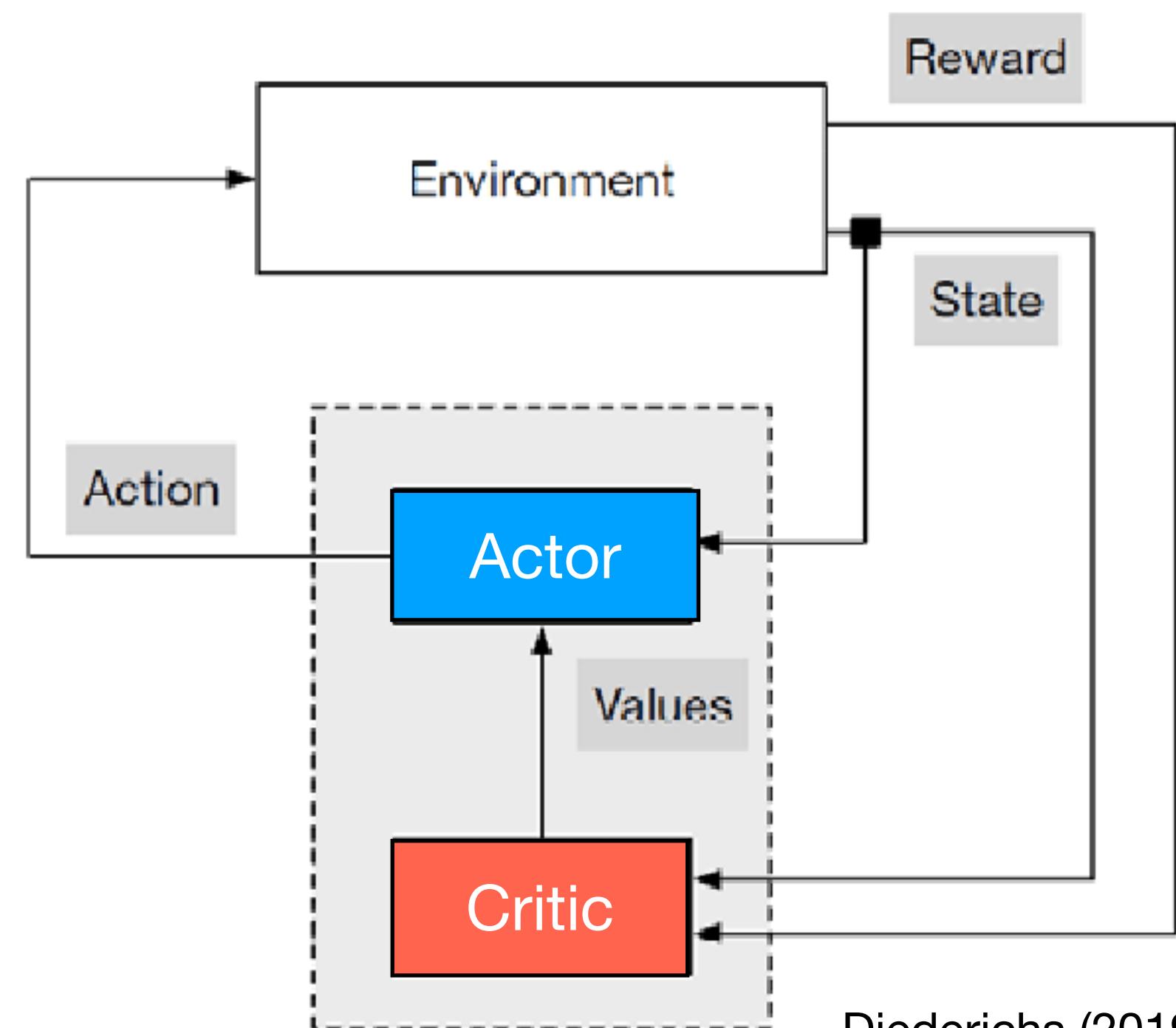
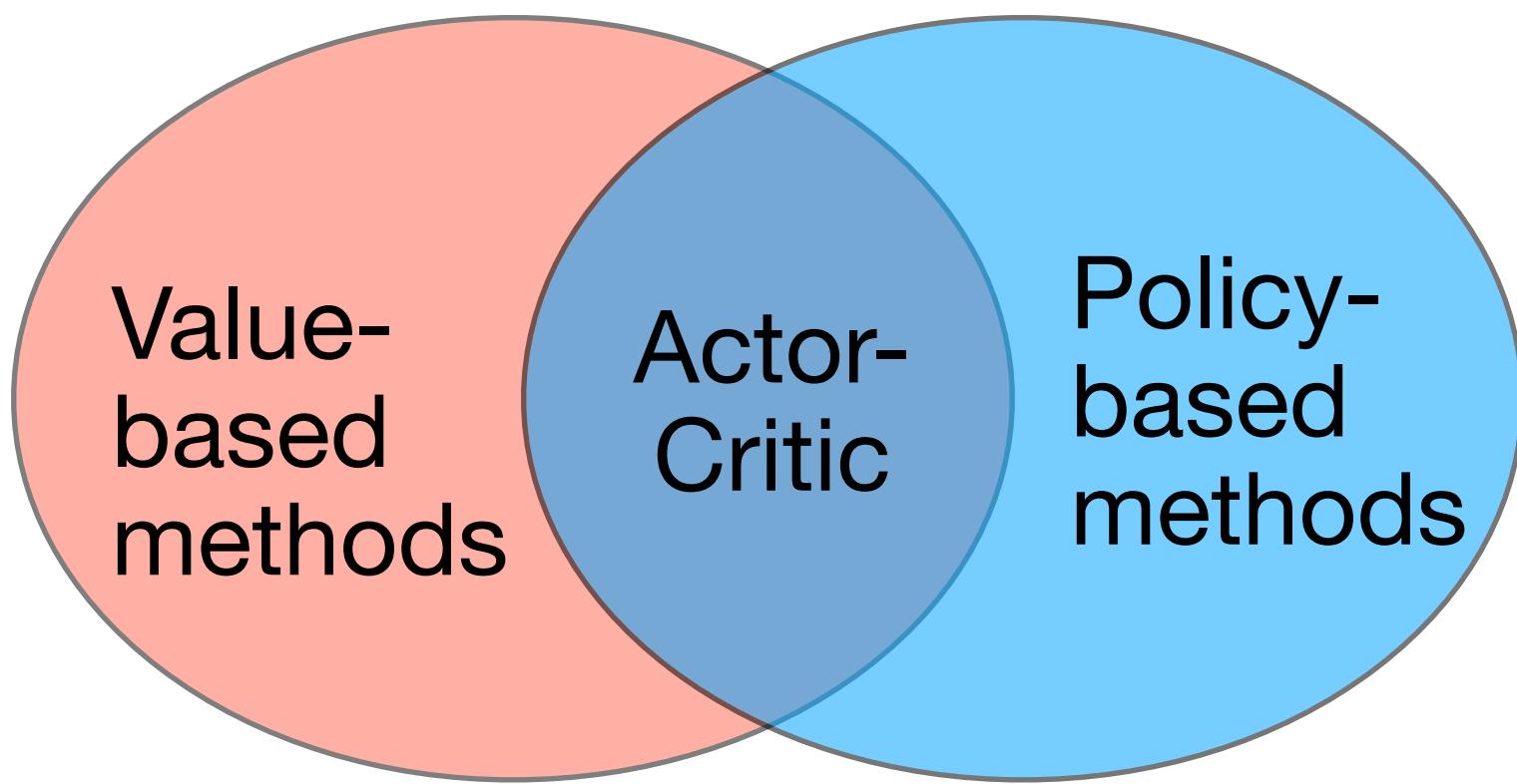
Diederichs (2019)

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 - **Critic** provides the value function $Q_w(s, a)$ parameterized by w

- Simulate trajectories $a \sim \pi_\theta(a | s)$ and compute TD error

$$\delta = r + \gamma \max_{a'} Q_w(s', a') - Q_w(s, a)$$

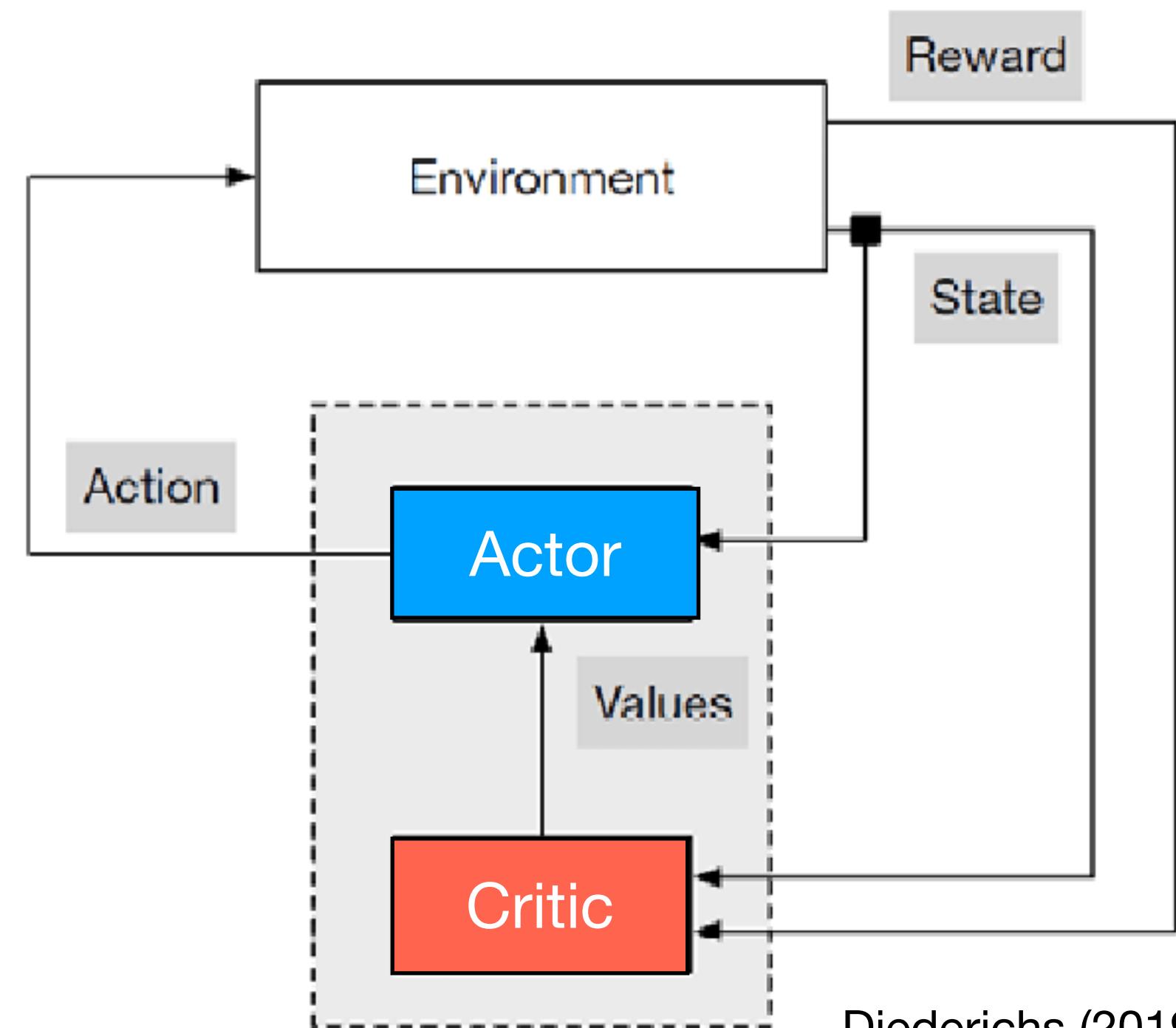
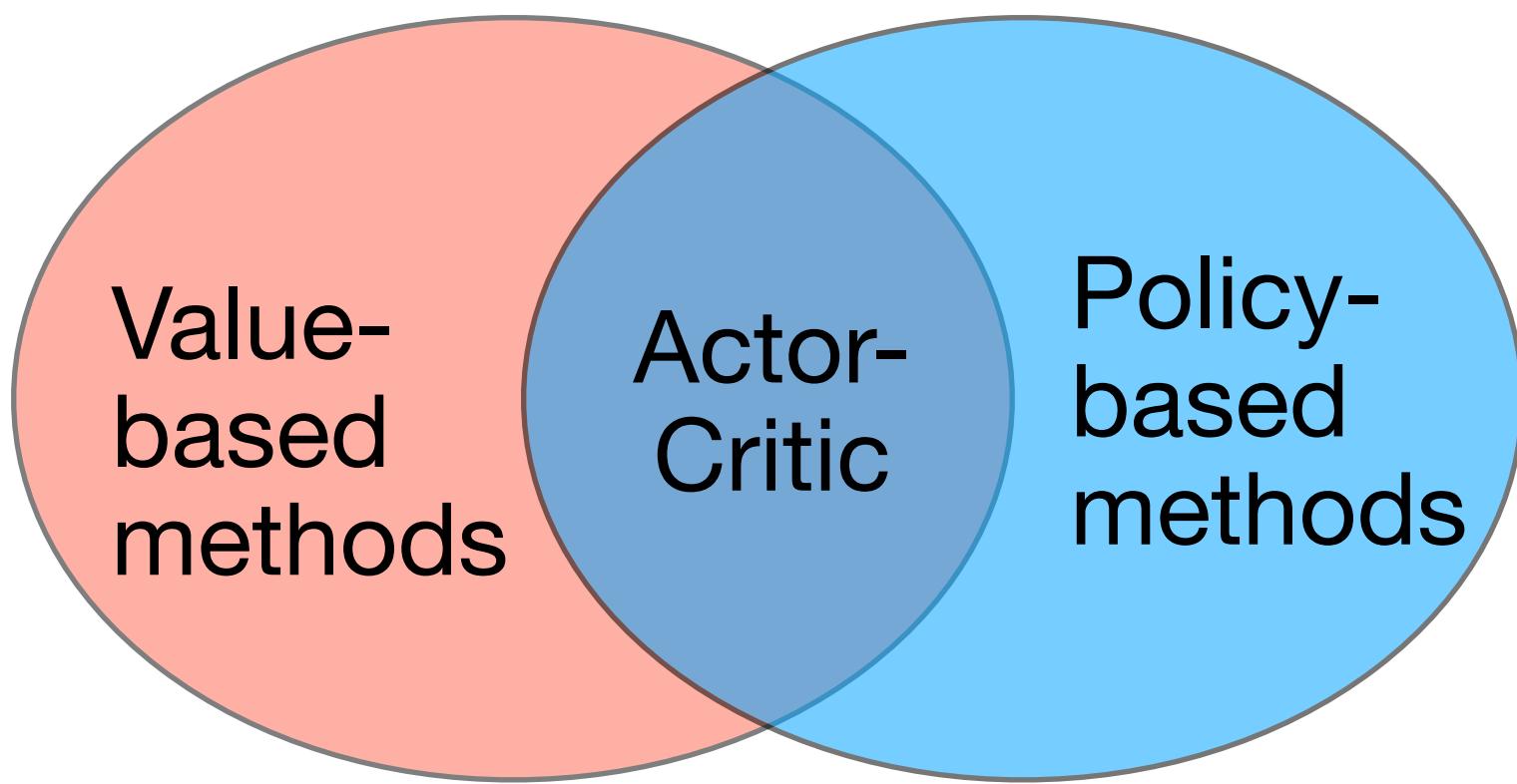


Diederichs (2019)

Actor-Critic

- Actor-critic combines **value-based** and **policy-based** methods and is a generalization of policy iteration
 - **Actor** provides the policy $\pi_\theta(a | s)$ parameterized by θ
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- Iteratively update actor and critic



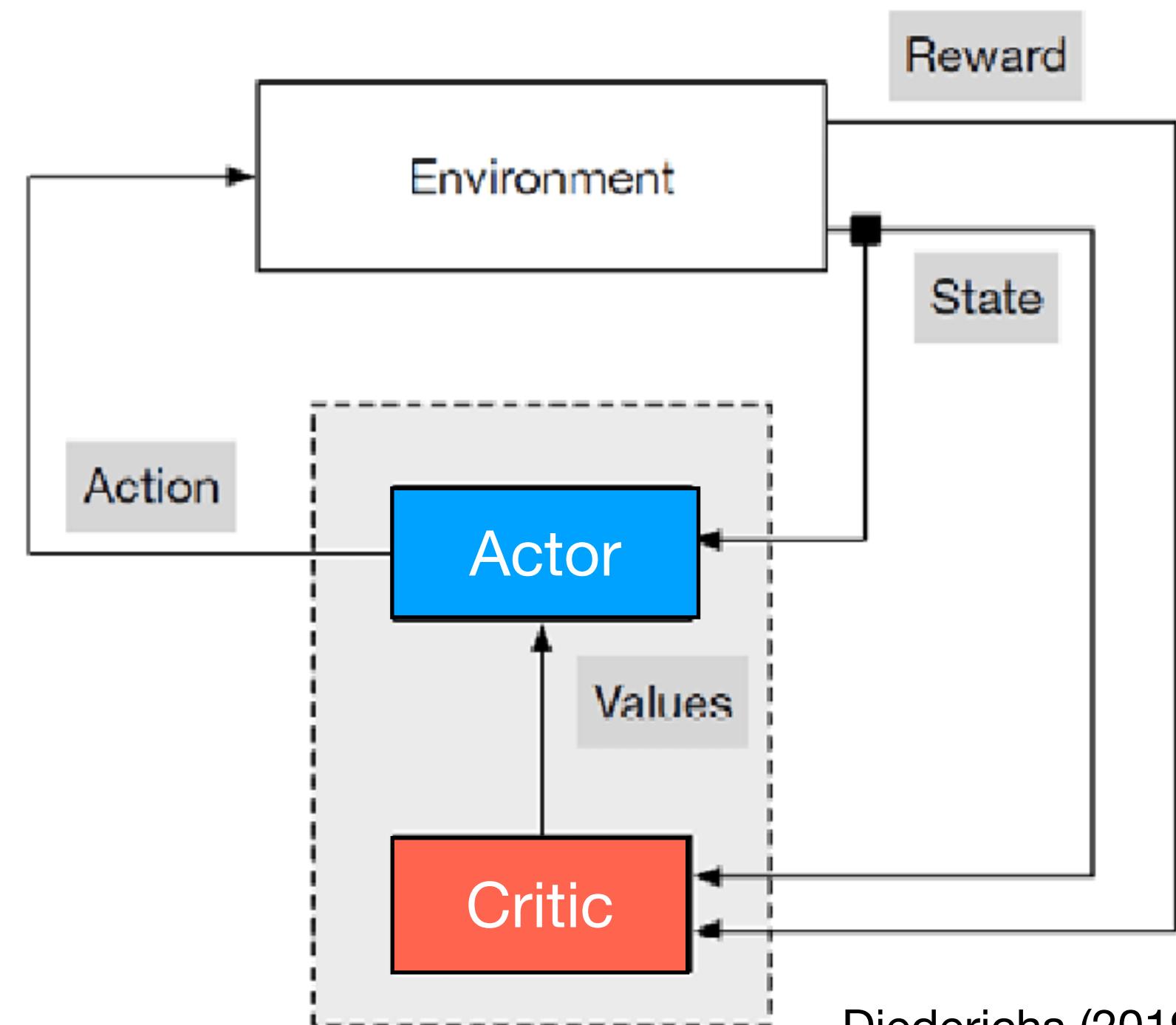
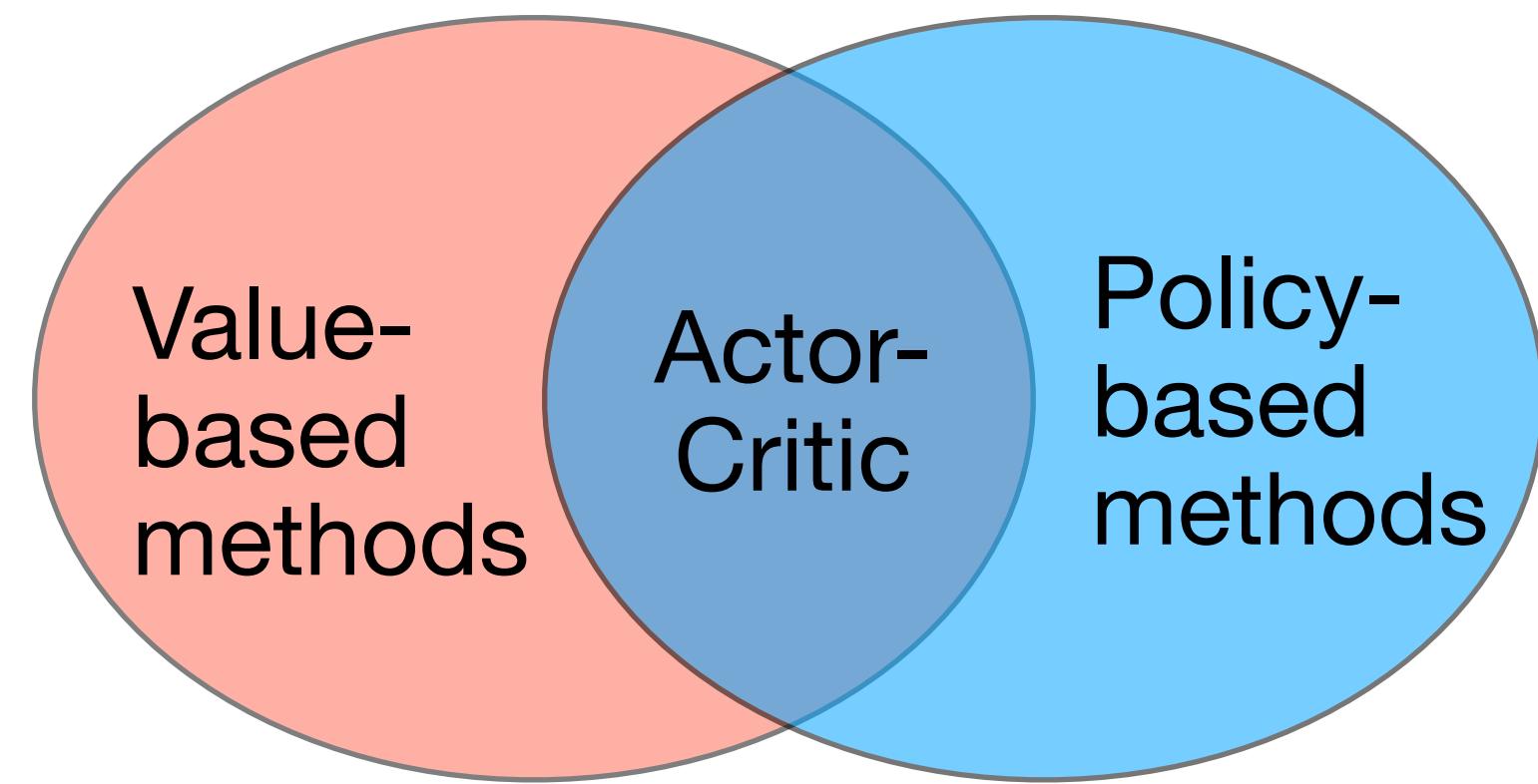
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reduce prediction error



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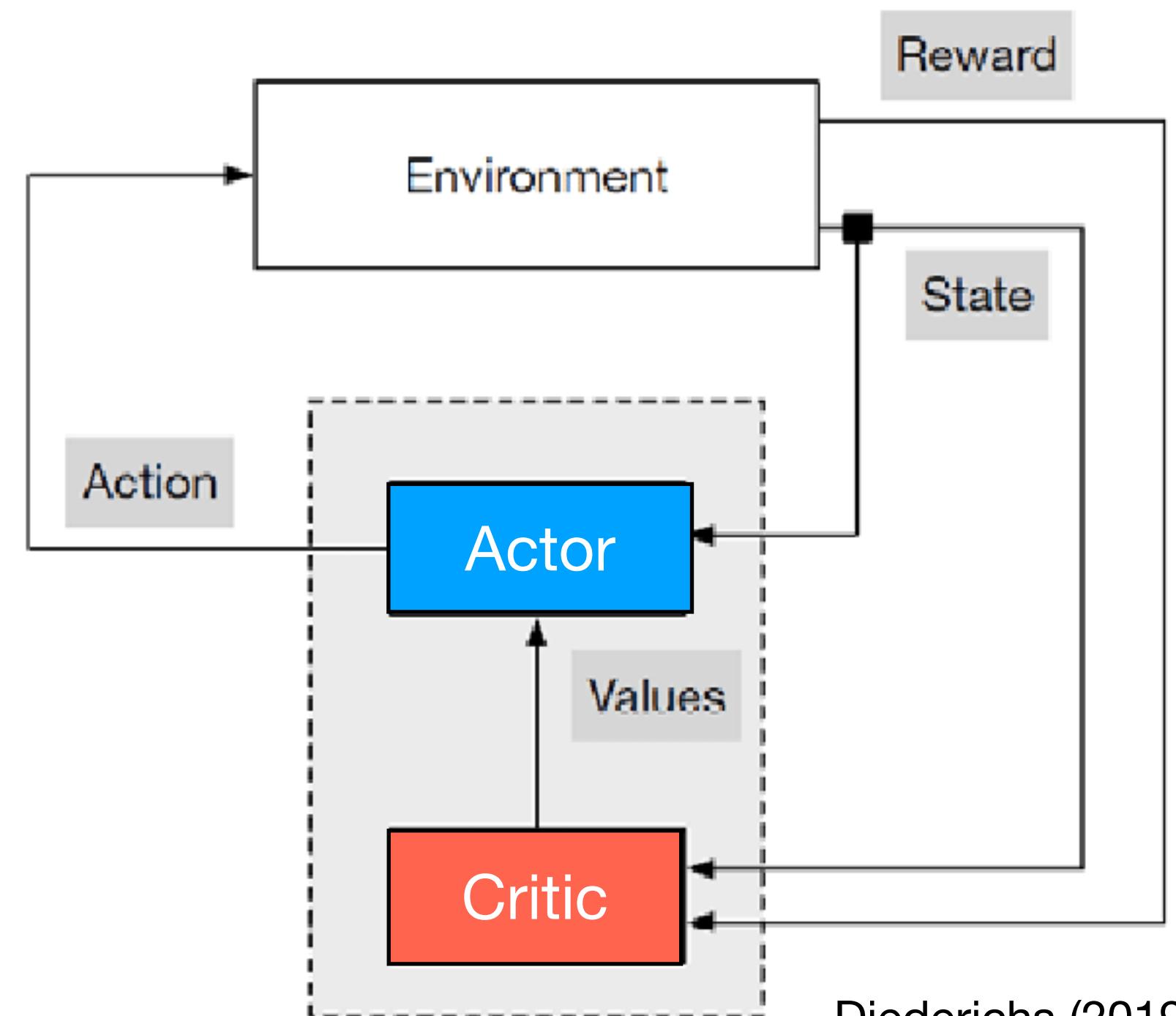
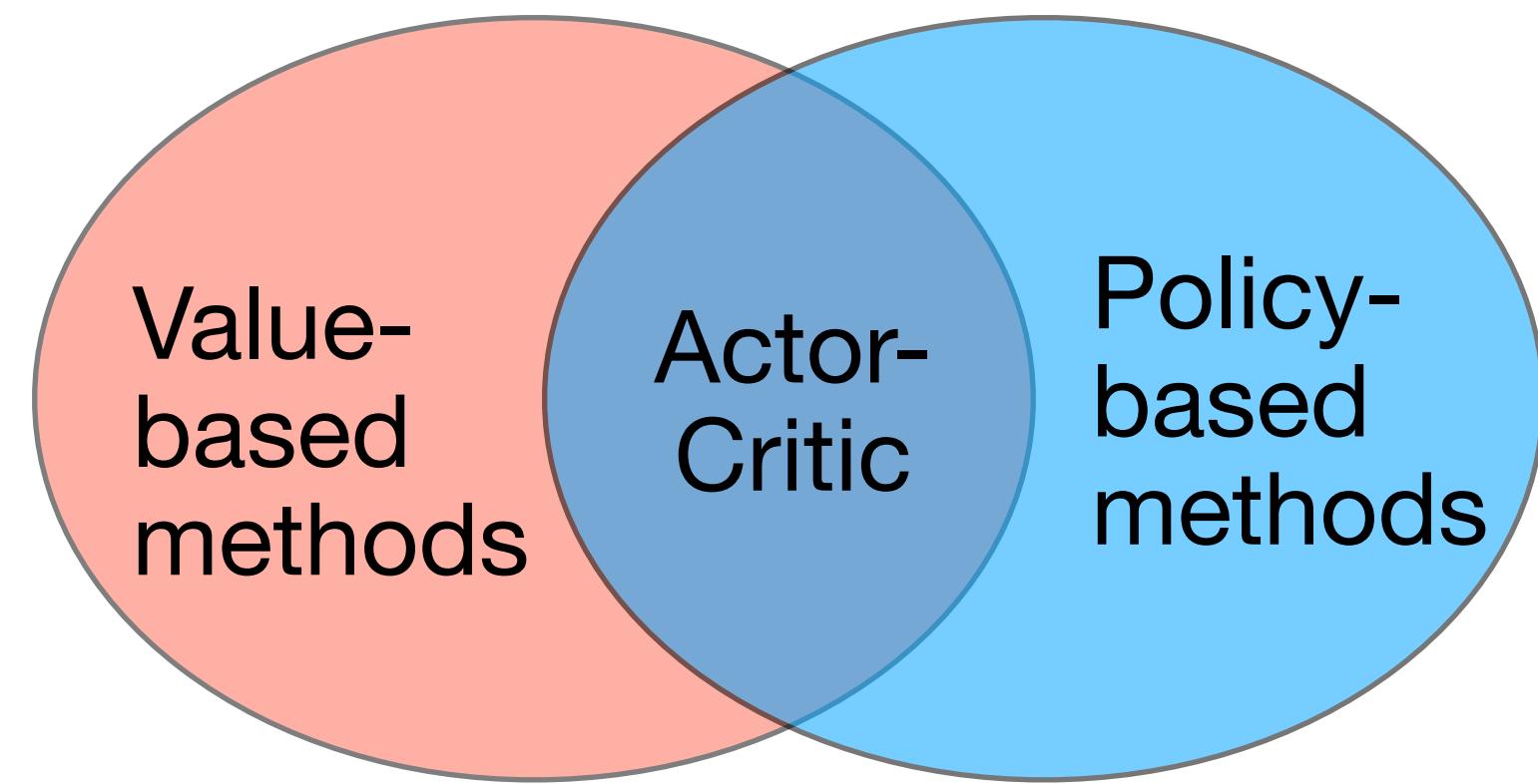
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reduce prediction error

- Actor update:** $\theta_{t+1} = \theta_t + \beta \delta \nabla_\theta \log \pi_\theta(a | s) Q_w(s, a)$
increase probability of highly rewarding actions



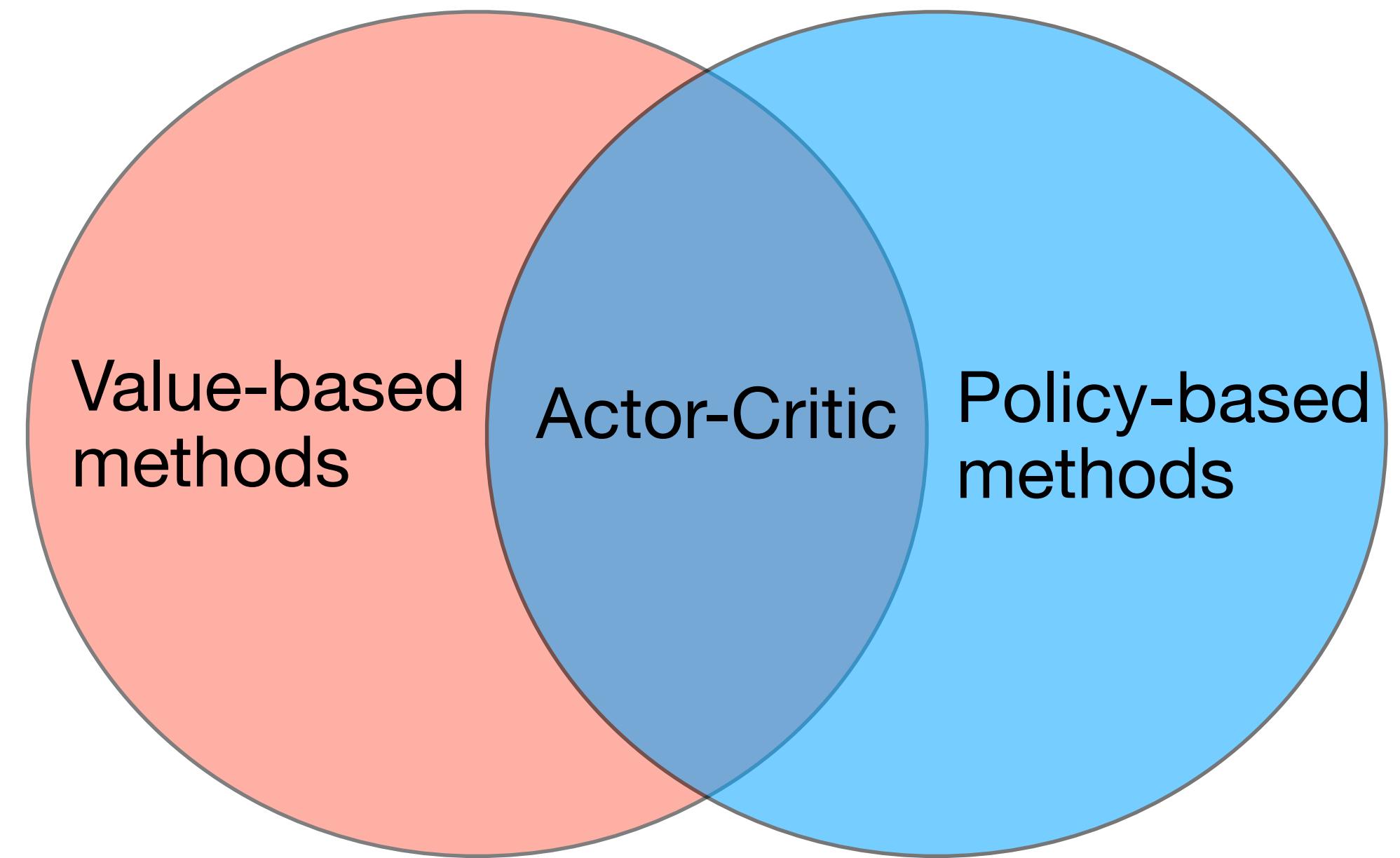
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Model-free methods summary

- Just put ANNs everywhere!
- **Value-based** methods
 - Deep Q Learning
- **Policy-based** methods
 - Policy Gradient
- **Actor-Critic**
 - Integration of both value-based and policy-based methods

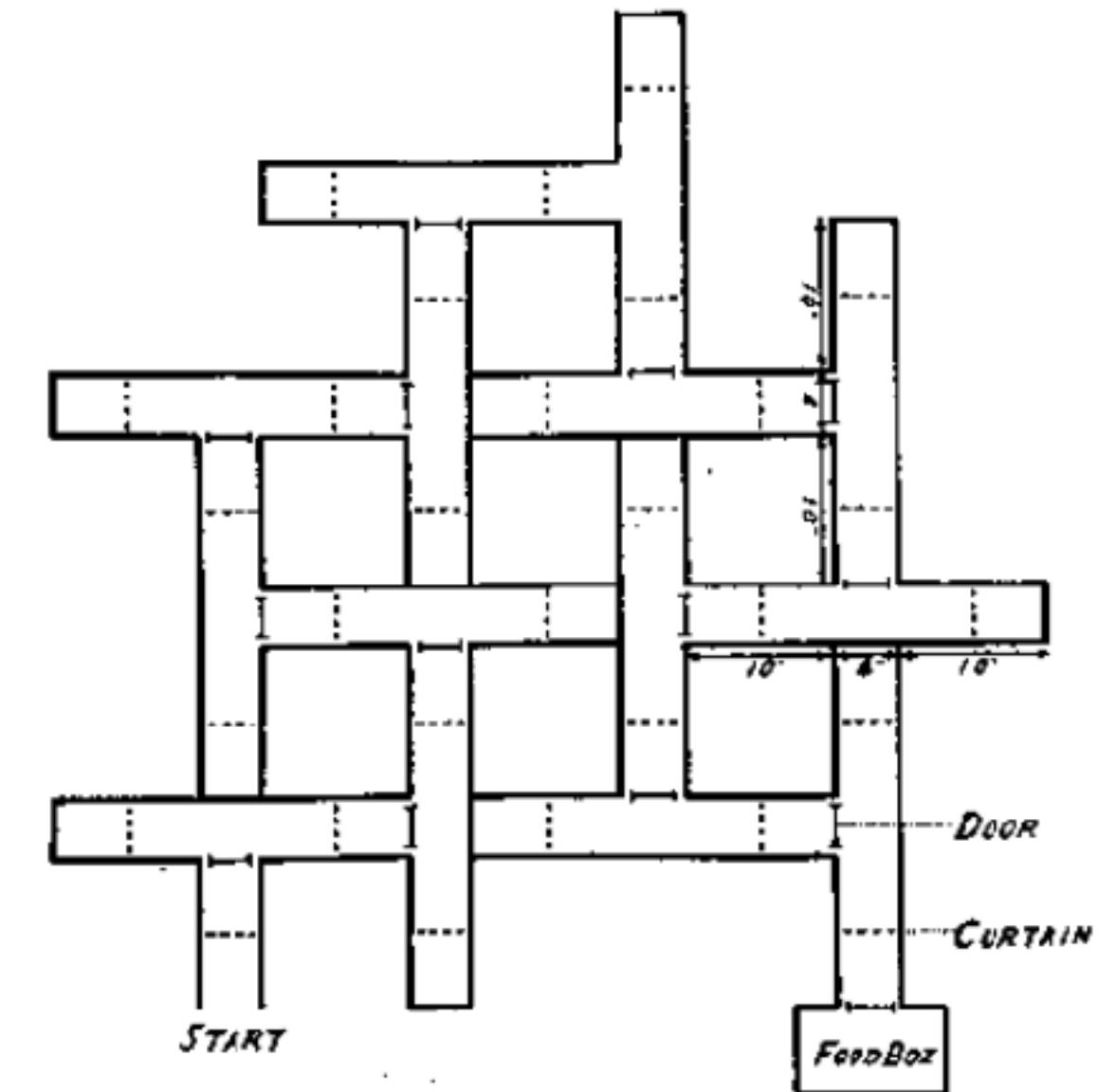
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Model-based methods

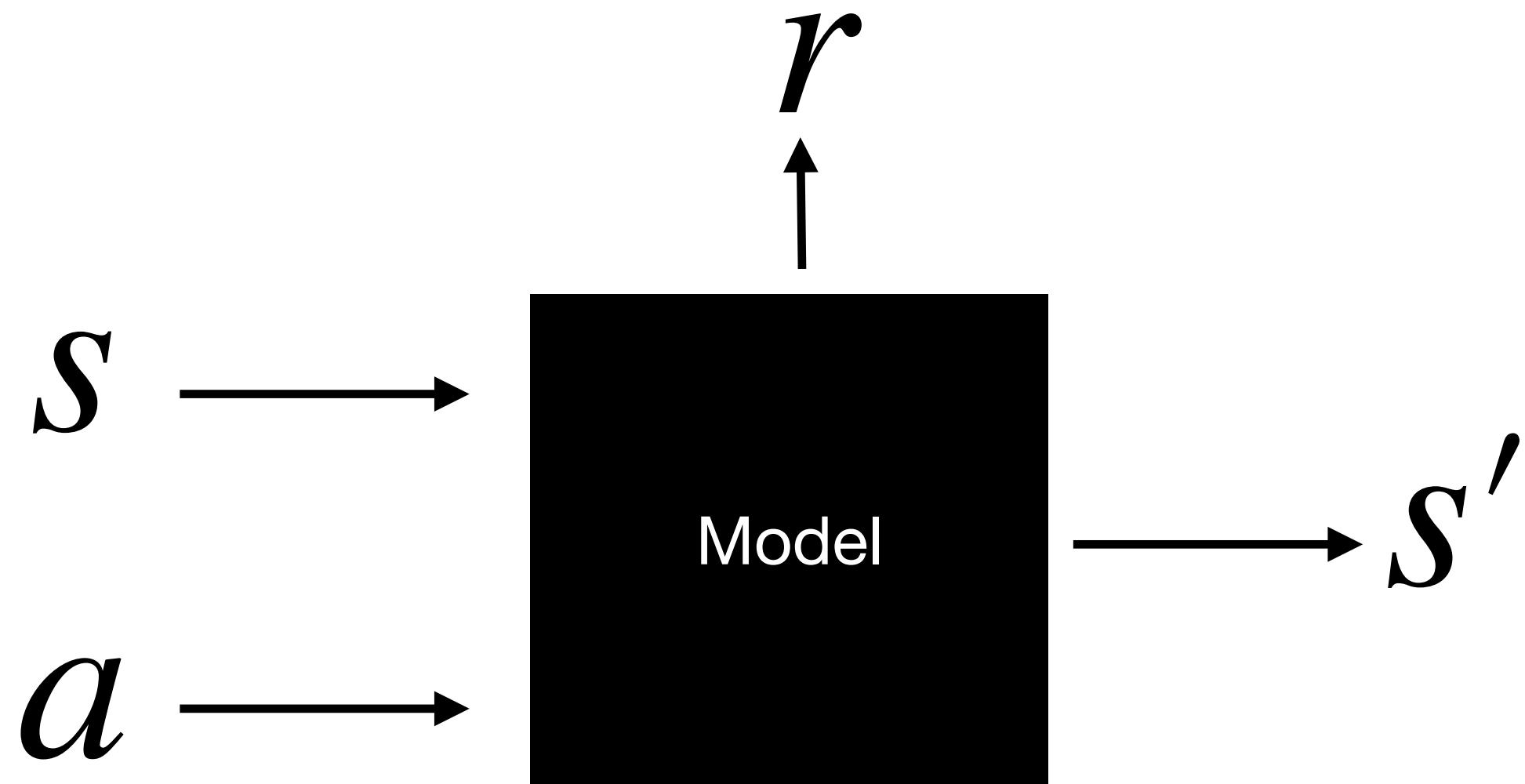
- Learning a “field map of the environment” helps with planning and generalization
- But how is the model learned?
- And how is it used to in RL?
- We will discuss
 - Learning transitions via Delta-Rule
 - DYNA for simulating experiences
 - World Models
 - Dreamer V3



Plan of maze
14-Unit T-Alley Maze

Fig. 1

(From M. H. Elliott, The effect of change of reward on the maze performance of rats. *Univ. Calif. Publ. Psychol.*, 1928, 4, p. 20.)



Learning the model through experience

- Follow whatever policy (e.g., random) and update the transition matrix using delta-rule

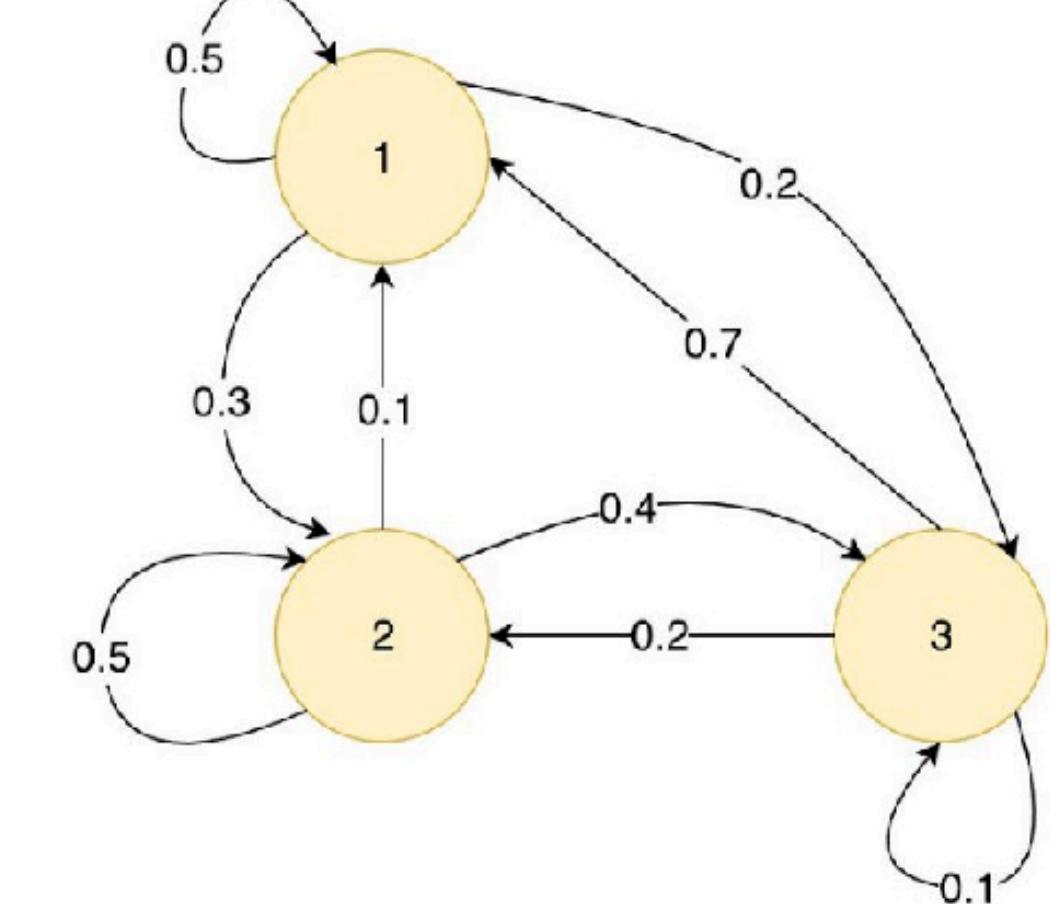
$$T_{t+1}(s'|s, a) \leftarrow T_t(s'|s, a) + \alpha (\delta(s', s) - T_t(s'|s, a))$$

- Kronecker delta $\delta(s', s') = 1$ when the transition occurs (i.e., $s \rightarrow s'$)
- $Model(s, a) \rightarrow [s', r]$ provided by learned transition matrix $T(s'|s, a)$ and value function $Q(s, a)$ or $V(s)$

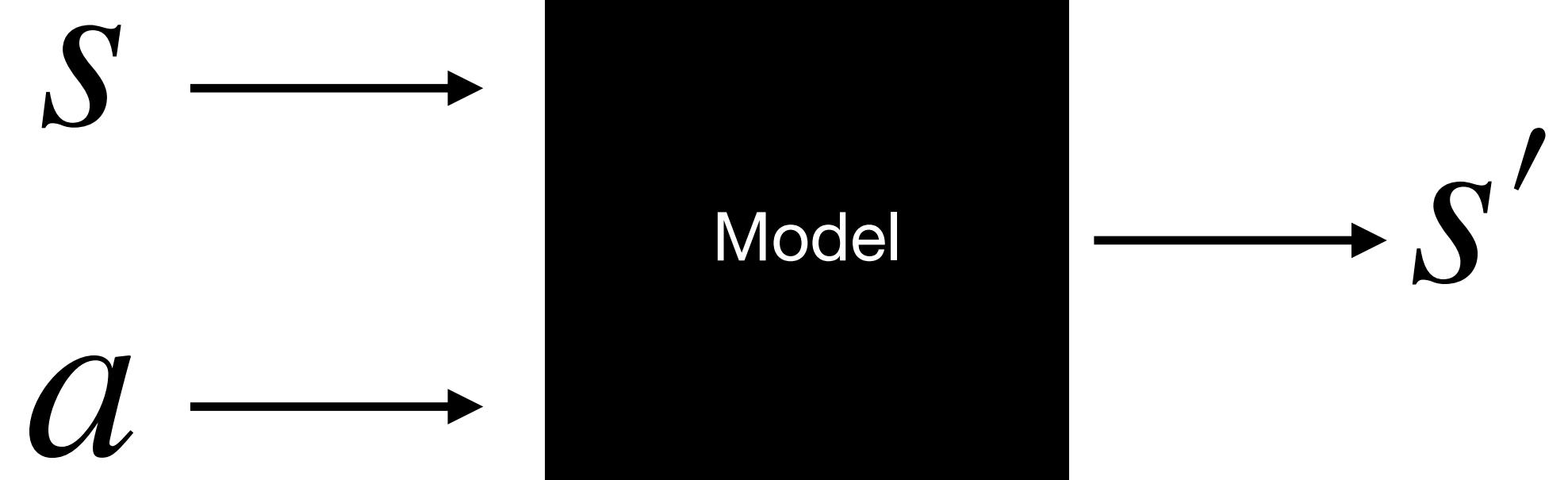
Transition Matrix

$$\begin{matrix} & s_1 & s_2 & s_3 \\ s_1 & \begin{bmatrix} 0.5 & 0.1 & 0.7 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.4 & 0.1 \end{bmatrix} \\ s_2 & & \\ s_3 & & \end{matrix}$$

MDP



r
↑



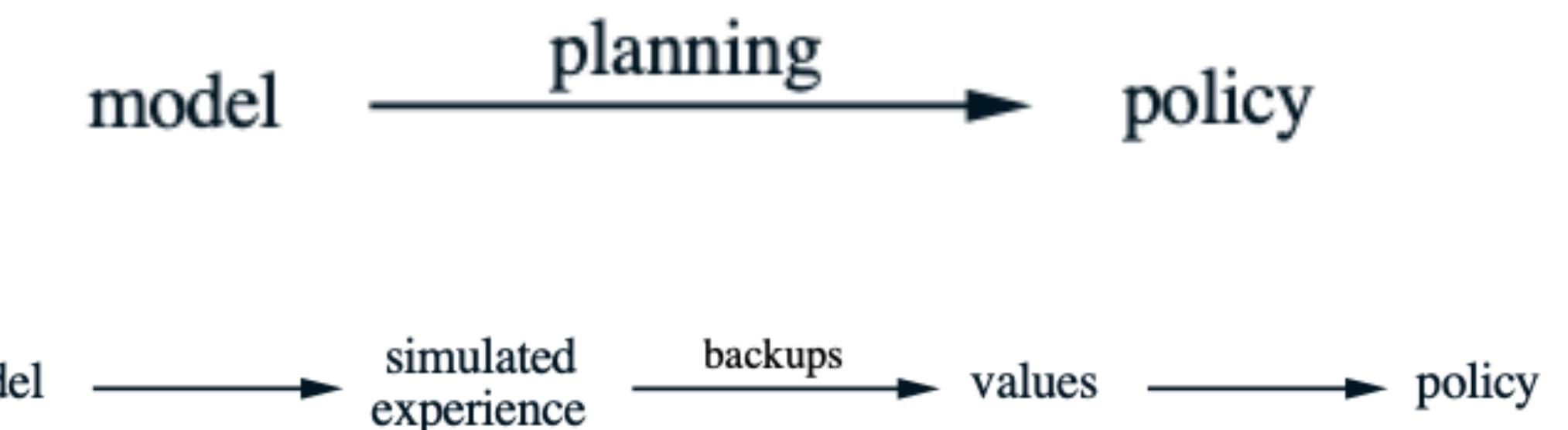
Simulating experiences with DYNA

- Models of the environment can be used for planning



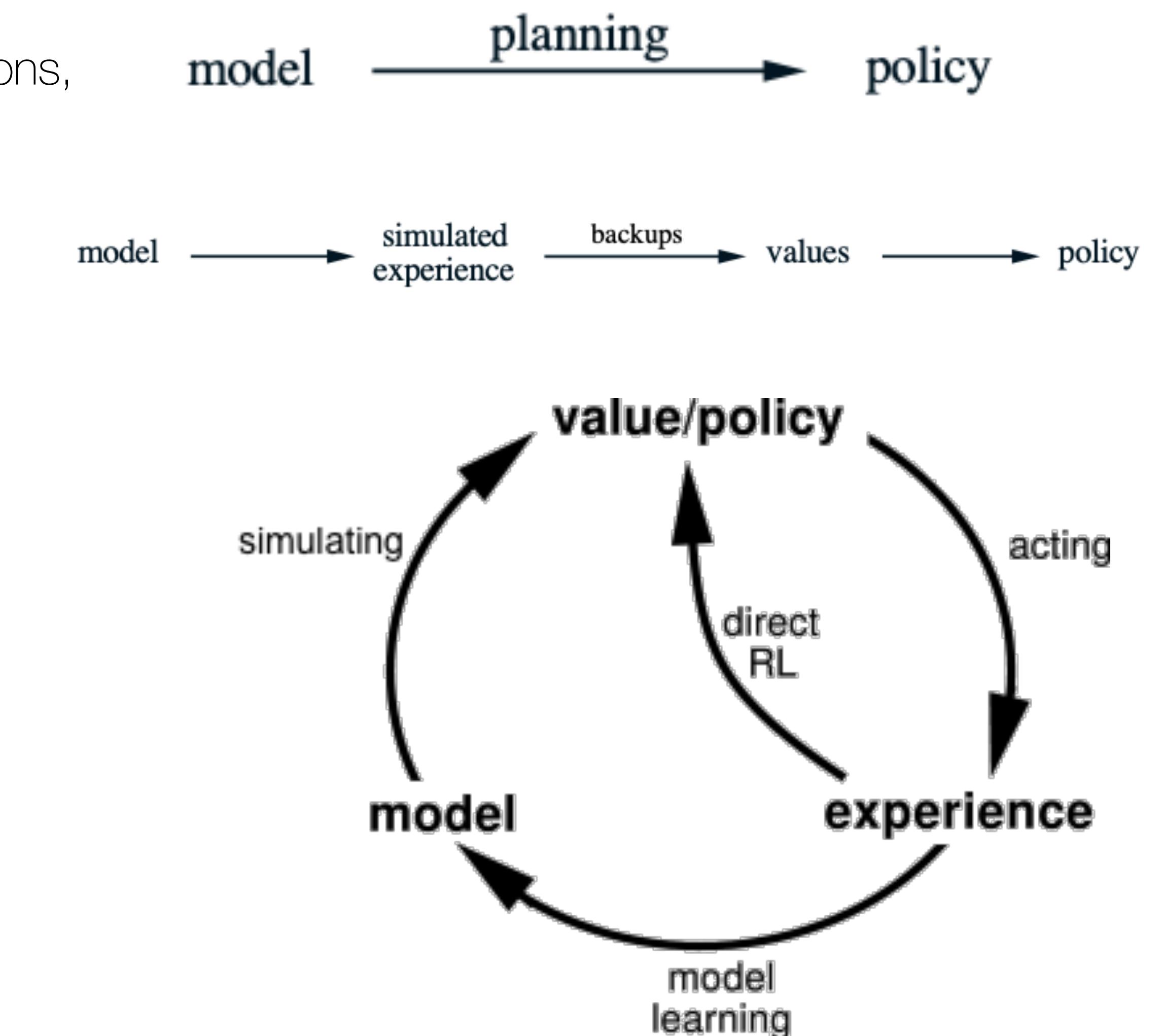
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- DYNA uses simulated experiences to update policy/value functions, just like real experiences



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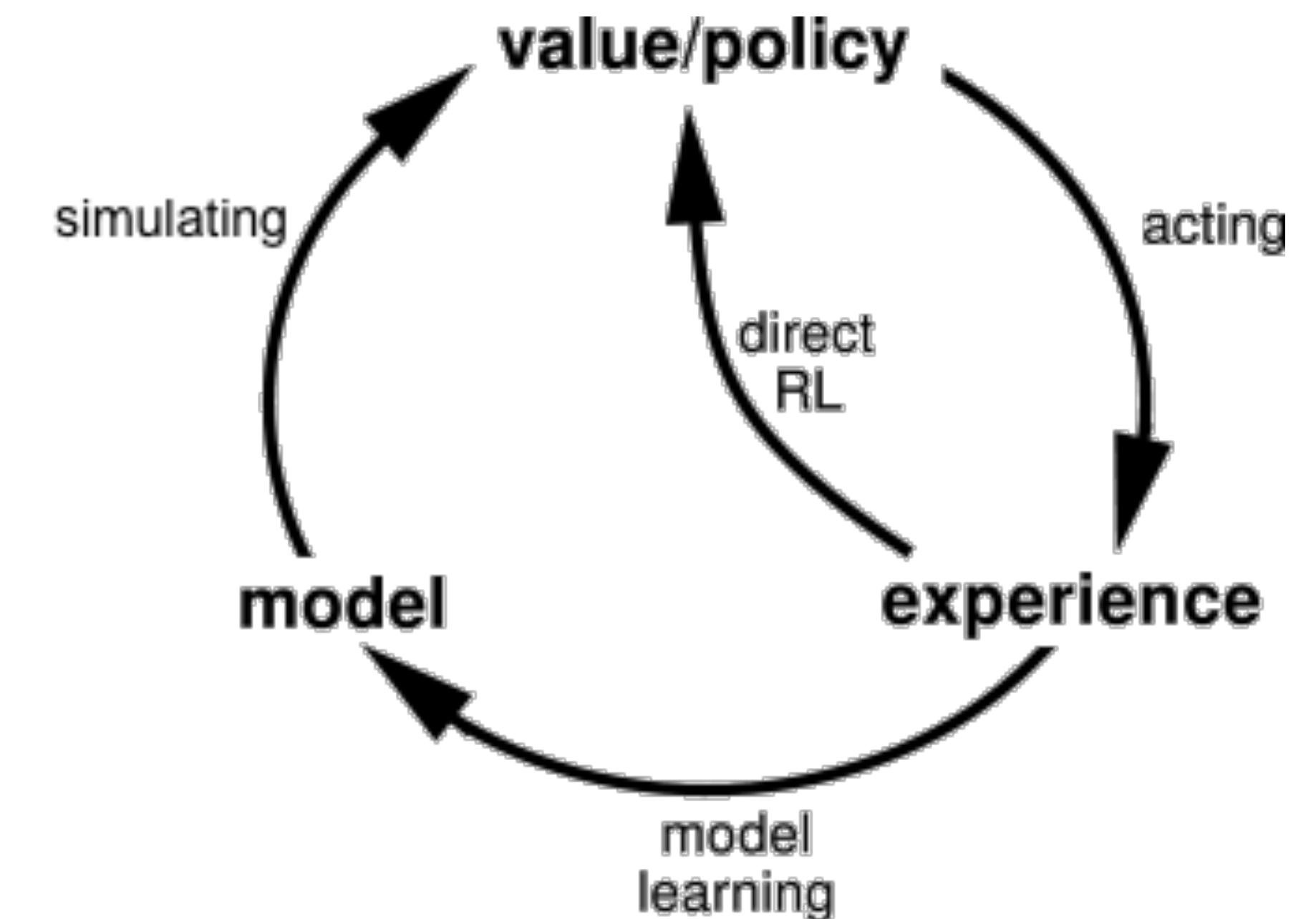
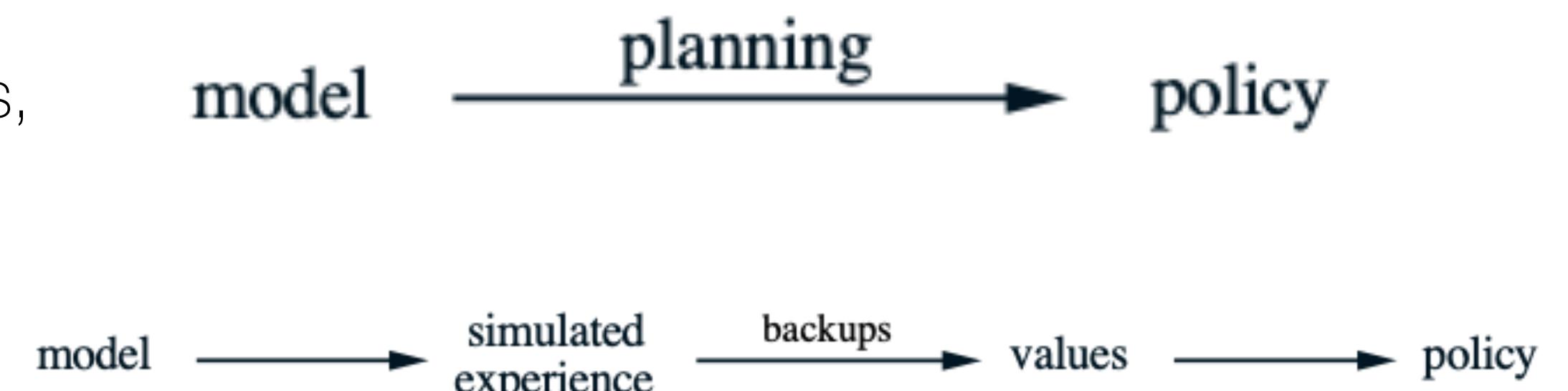


Simulating experiences with DYNA

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1. **Direct RL**: Execute real actions and update value function

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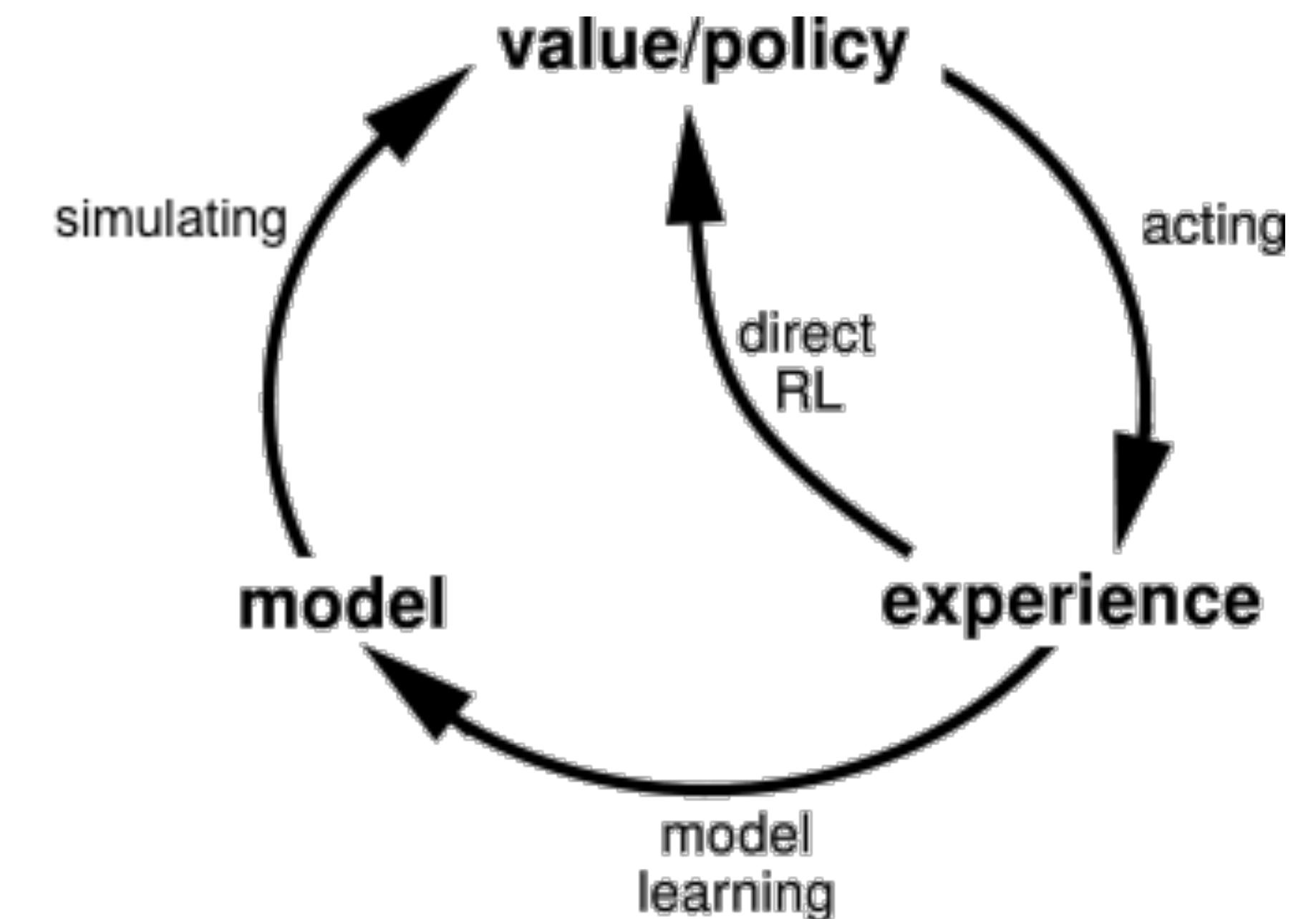
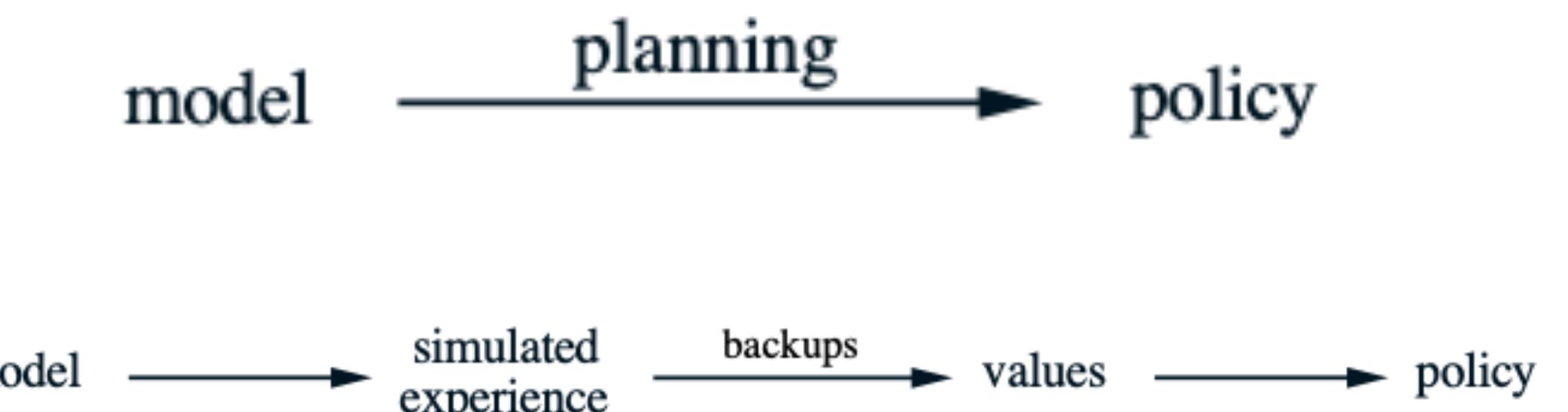
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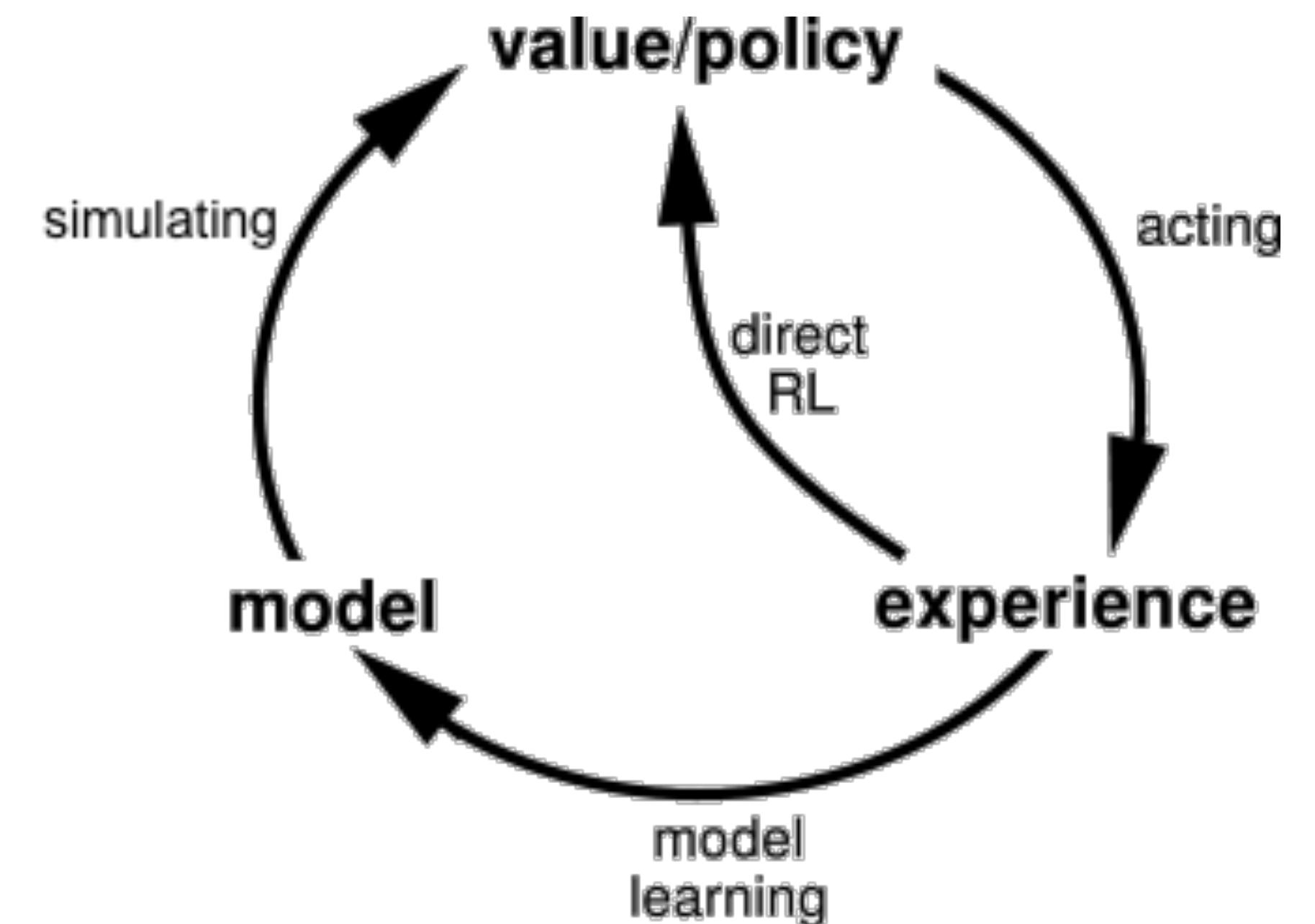
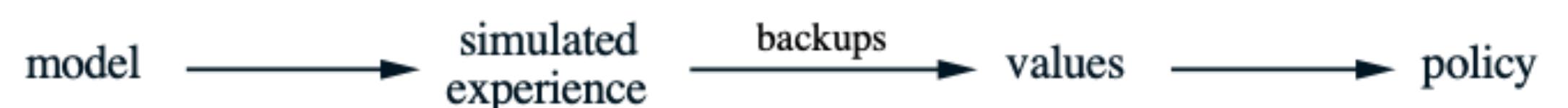
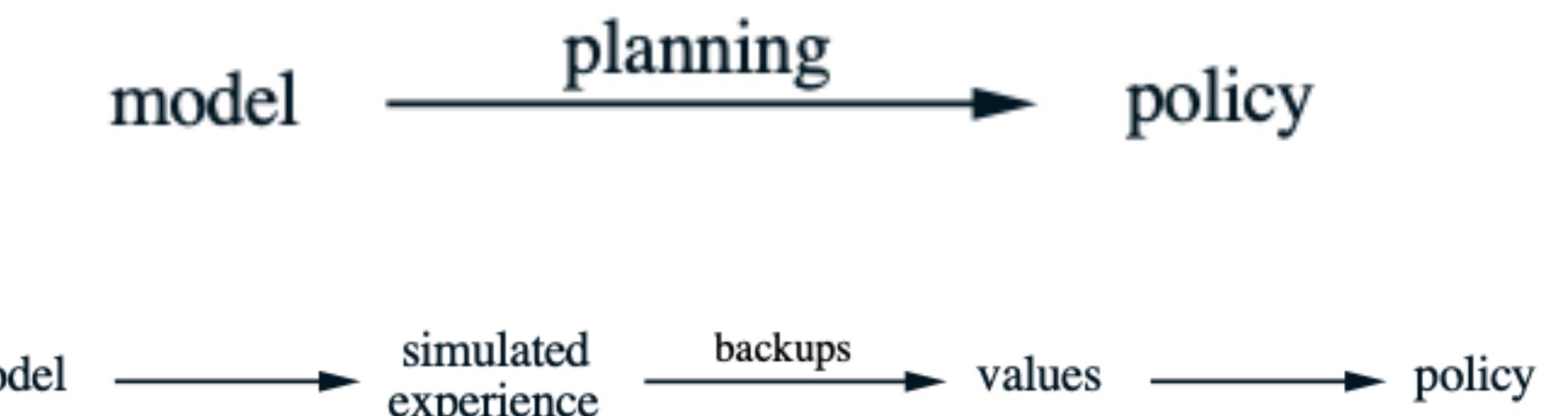
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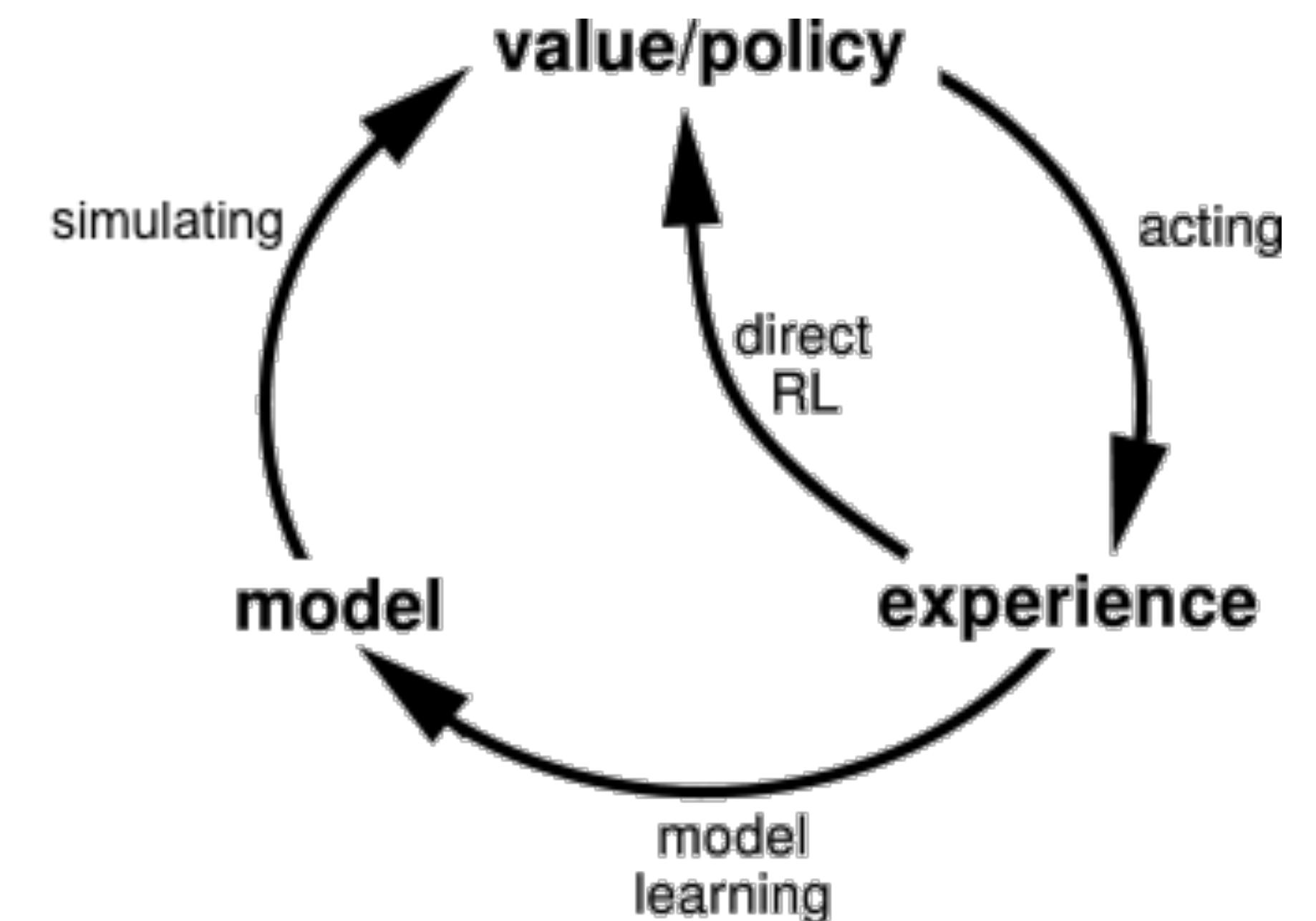
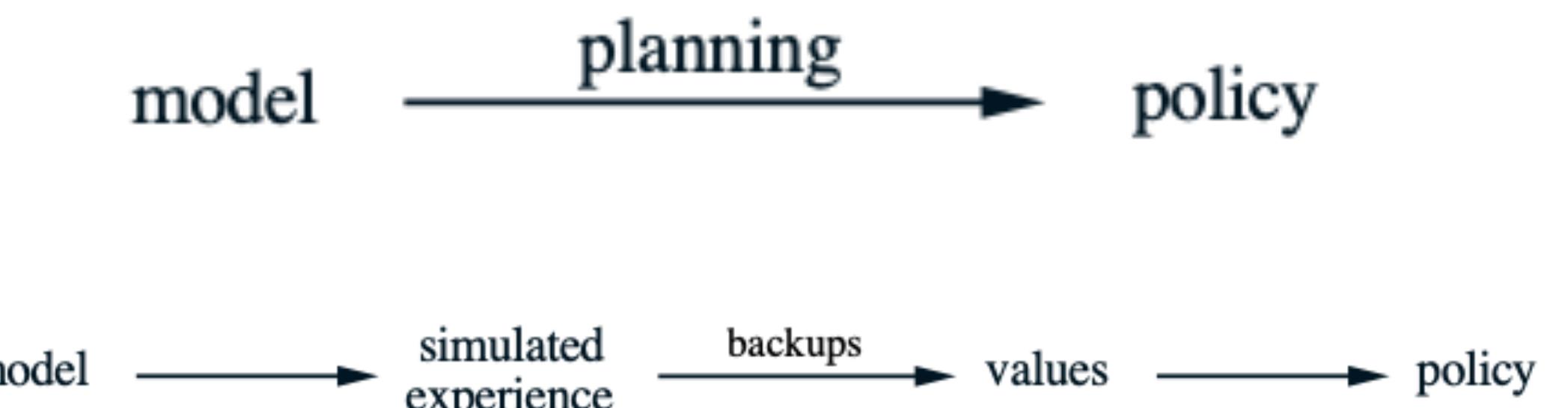
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Simulating experiences with DYNA

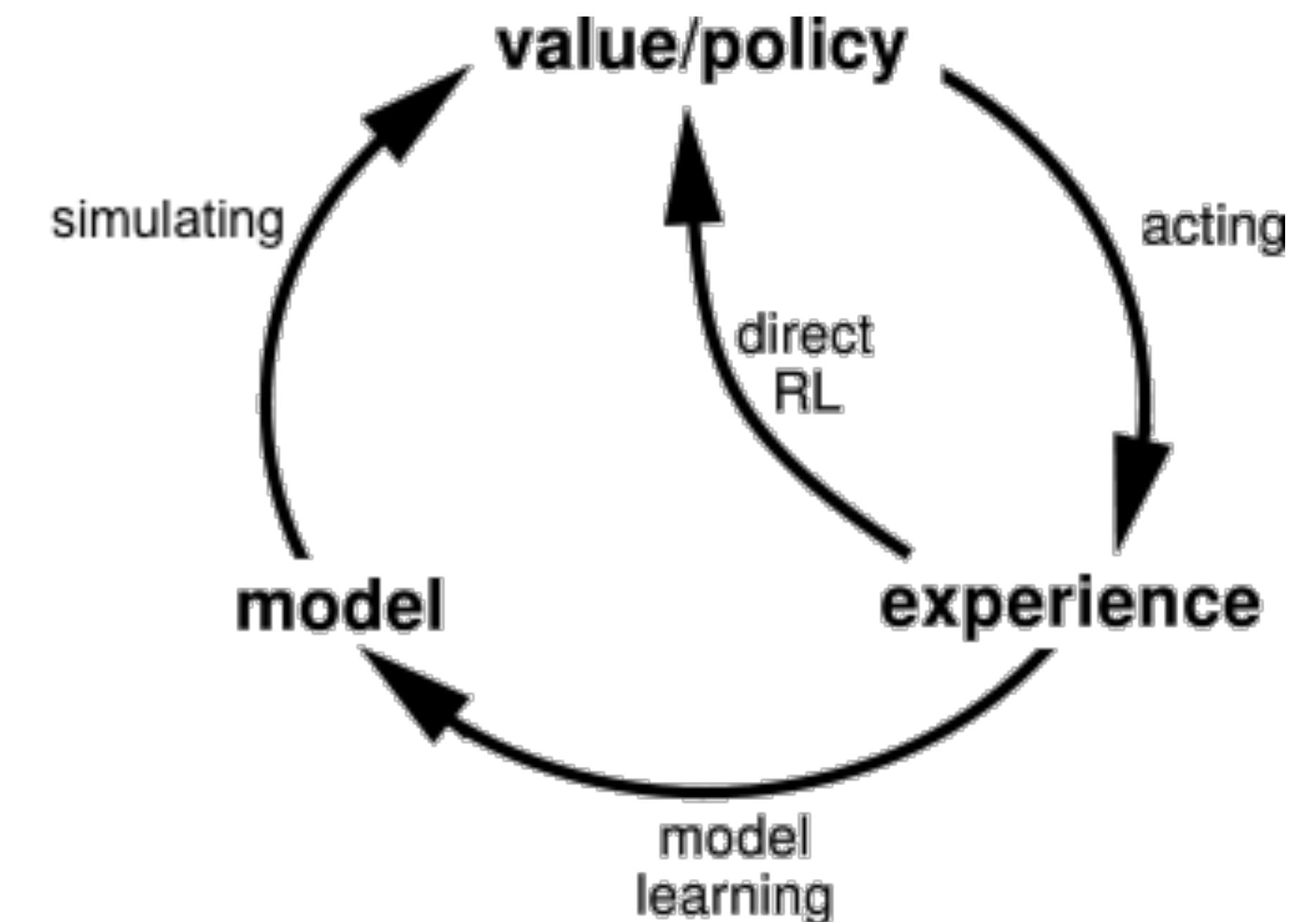
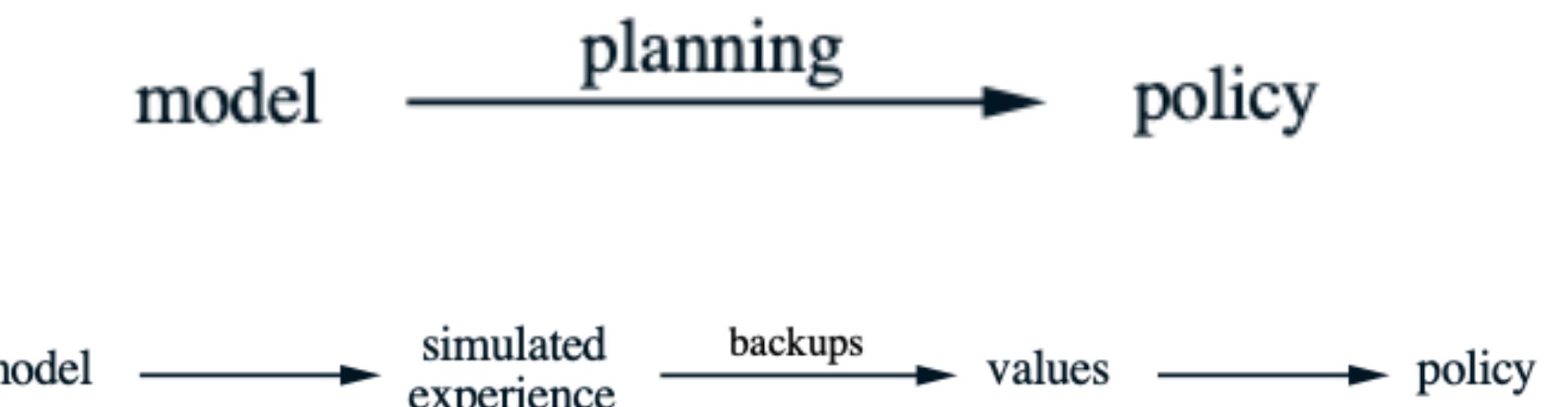
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 - Give previously observed states and actions to model
 $[s, a] \rightarrow Model(s, a) \rightarrow [s', r]$



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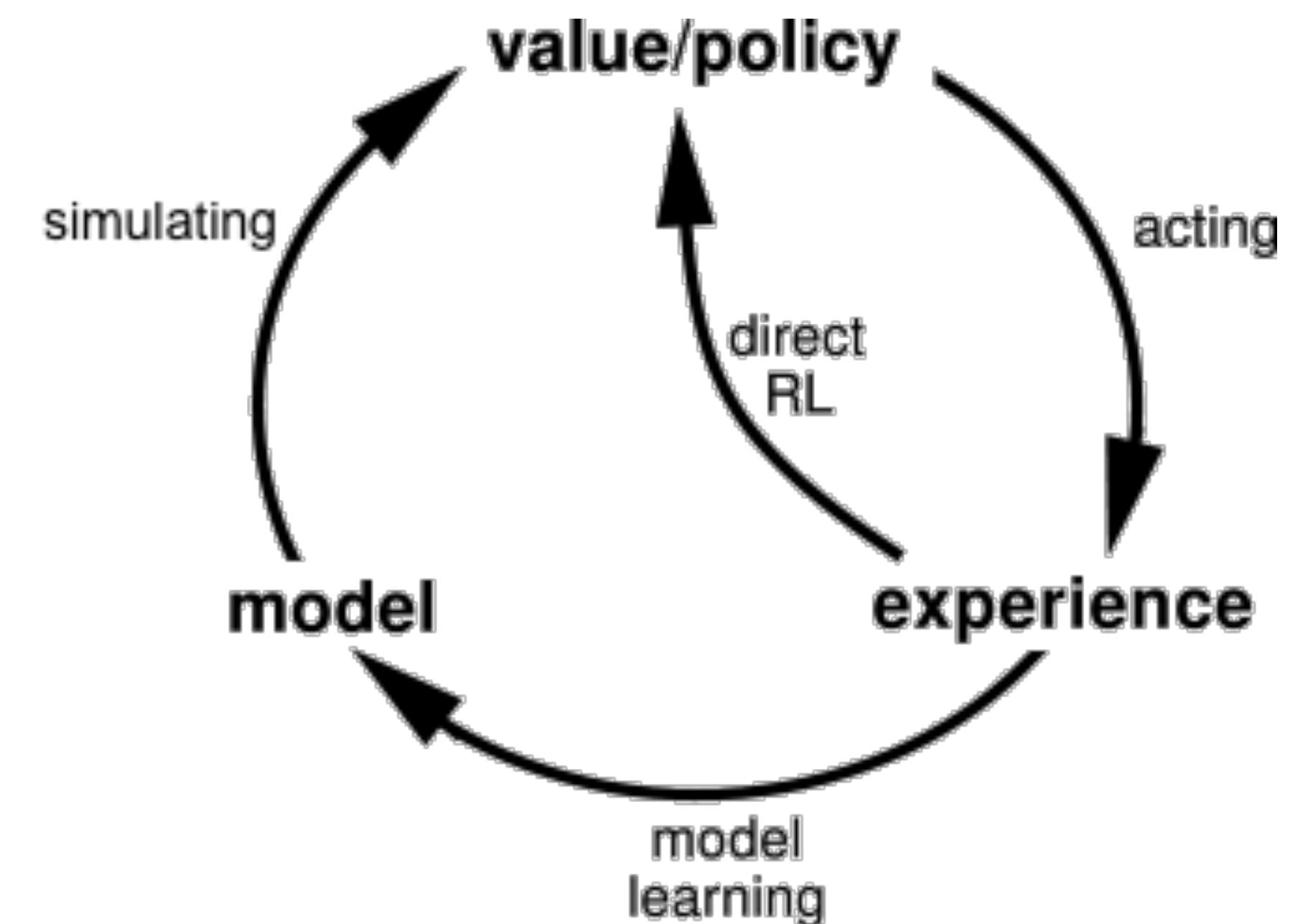
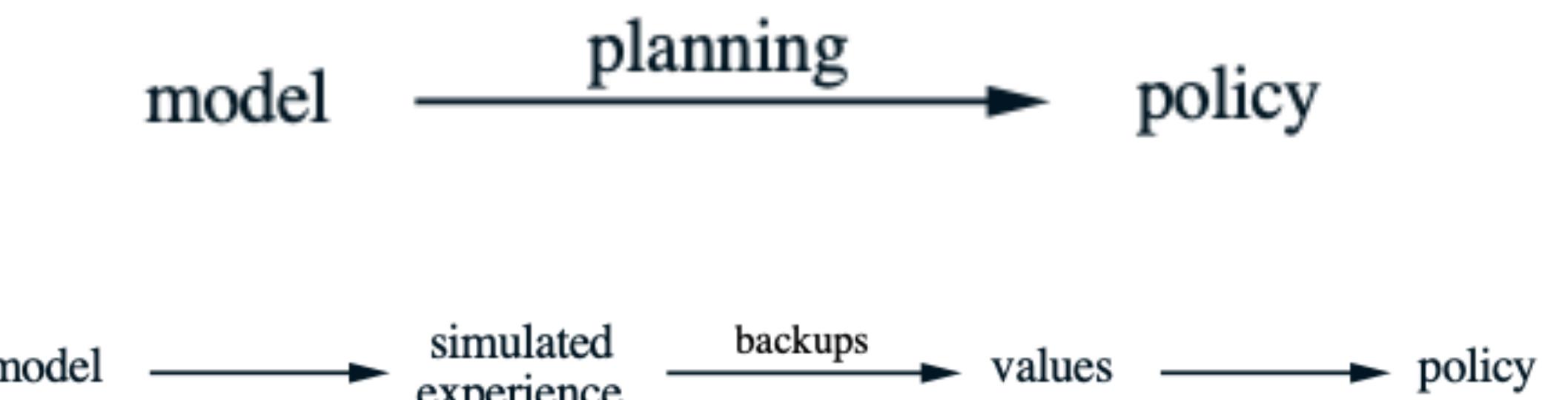
b. Simulate experiences:

- Give previously observed states and actions to model

$$[s, a] \rightarrow Model(s, a) \rightarrow [s', r]$$

- Update value function with simulated experiences

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$$



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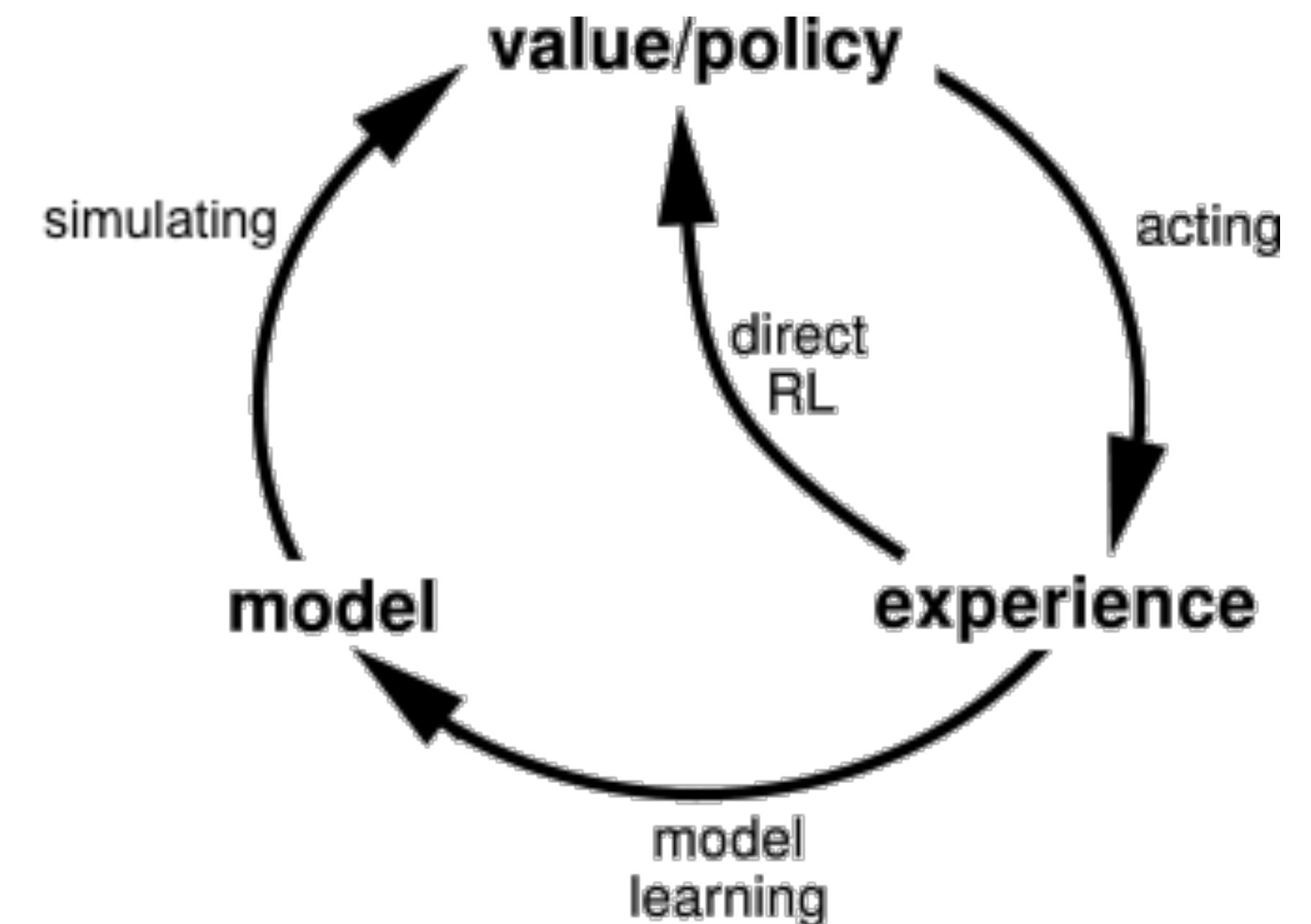
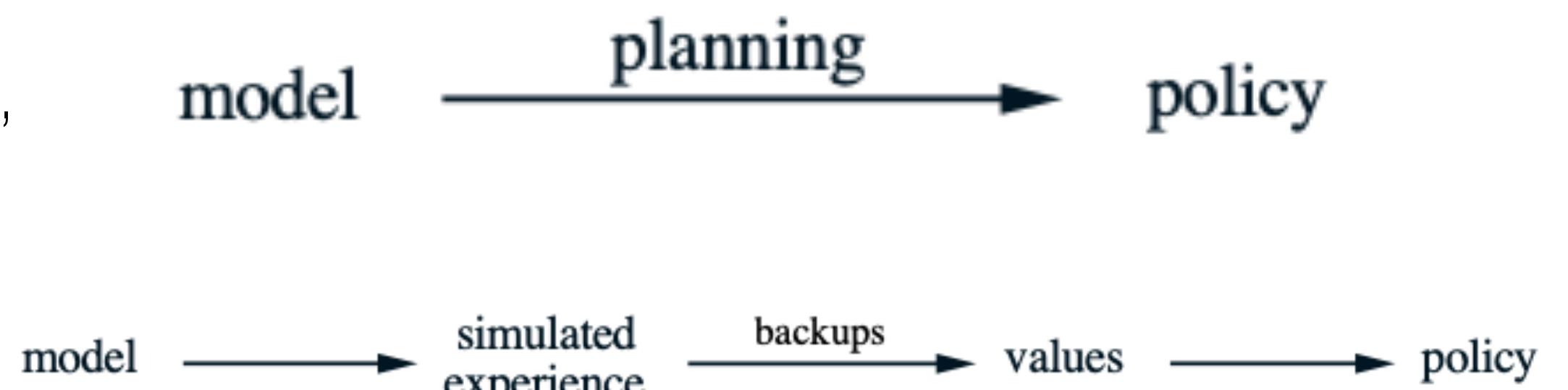
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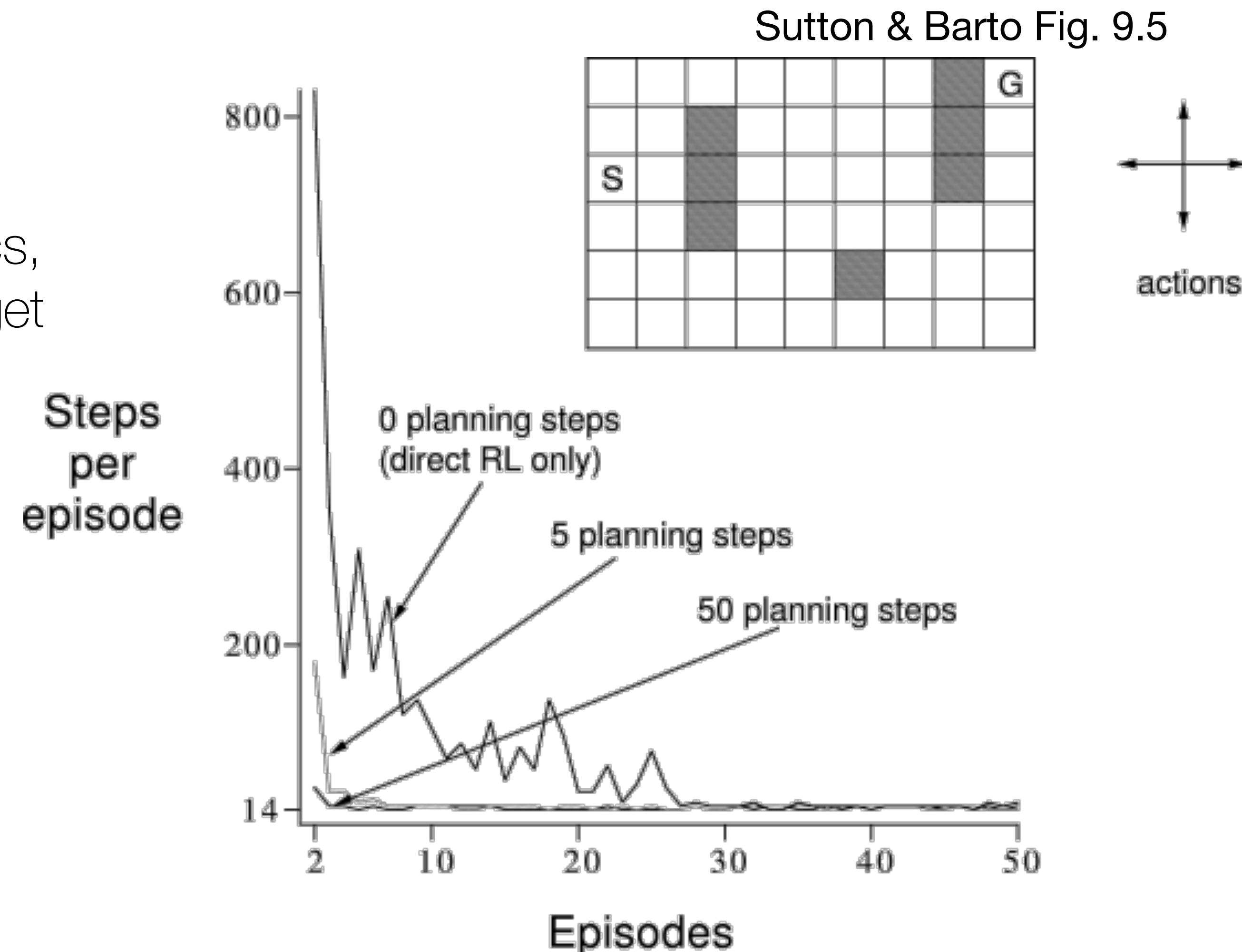
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- These simulations can be controlled for better efficiency (e.g., prioritized sweeps of reward-relevant state visitations; Moore & Atkeson, 1993)



Benefits of Model-based planning

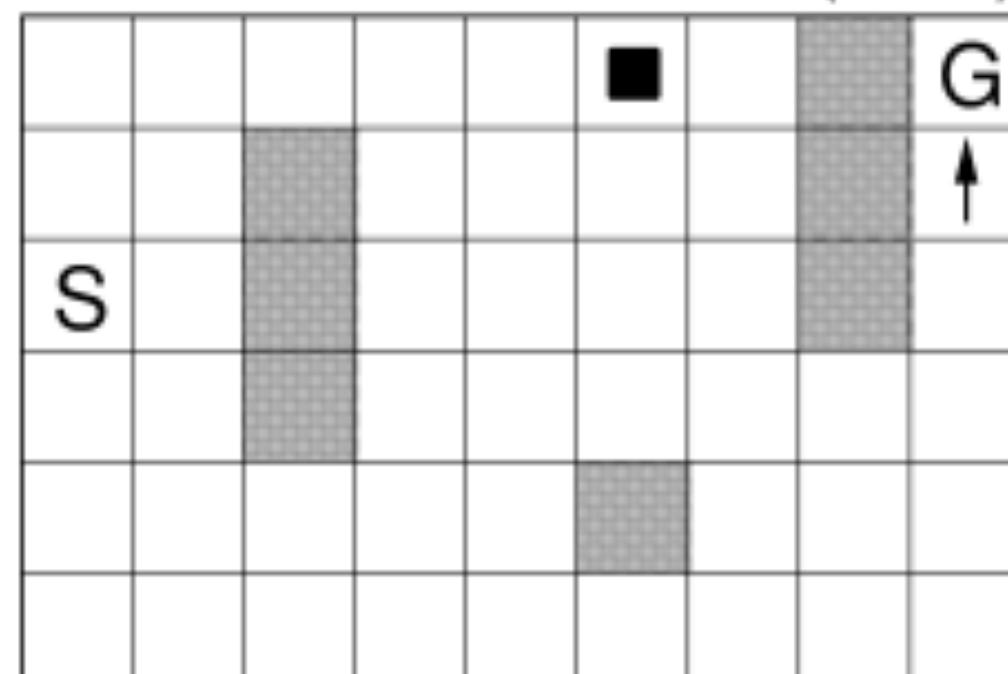
- Model-based planning needs far fewer real interactions with the environment (episodes) to learn better policies
 - Consider settings like self-driving cars, robotics, financial systems... where it is very costly to get real interaction data



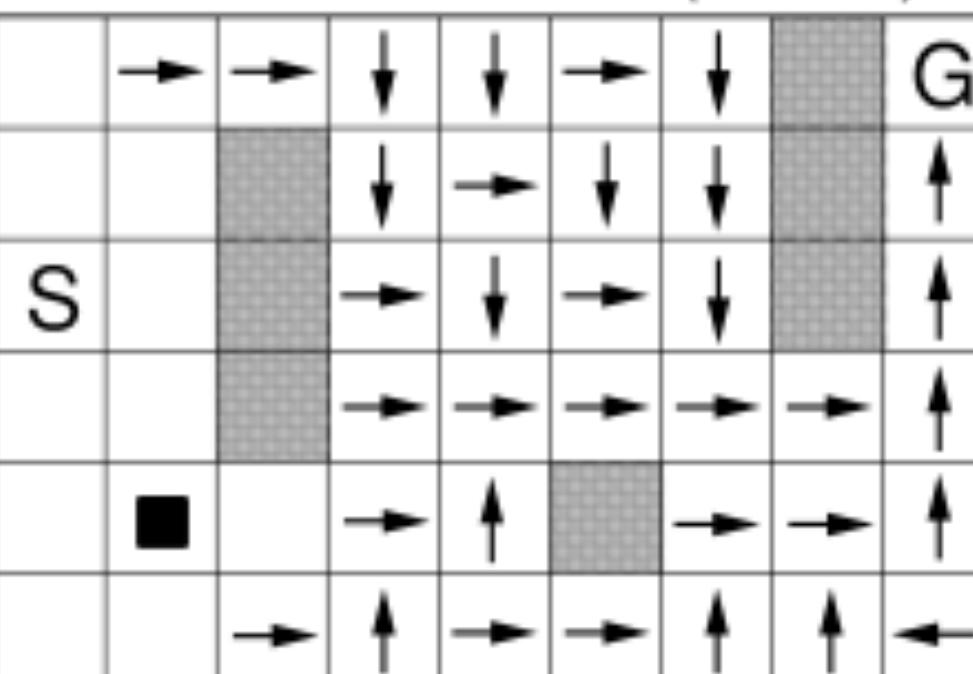
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- Halfway through only the 2nd episode...
 - Arrows show greedy action in each state and no arrow if all actions are equal

WITHOUT PLANNING ($N=0$)

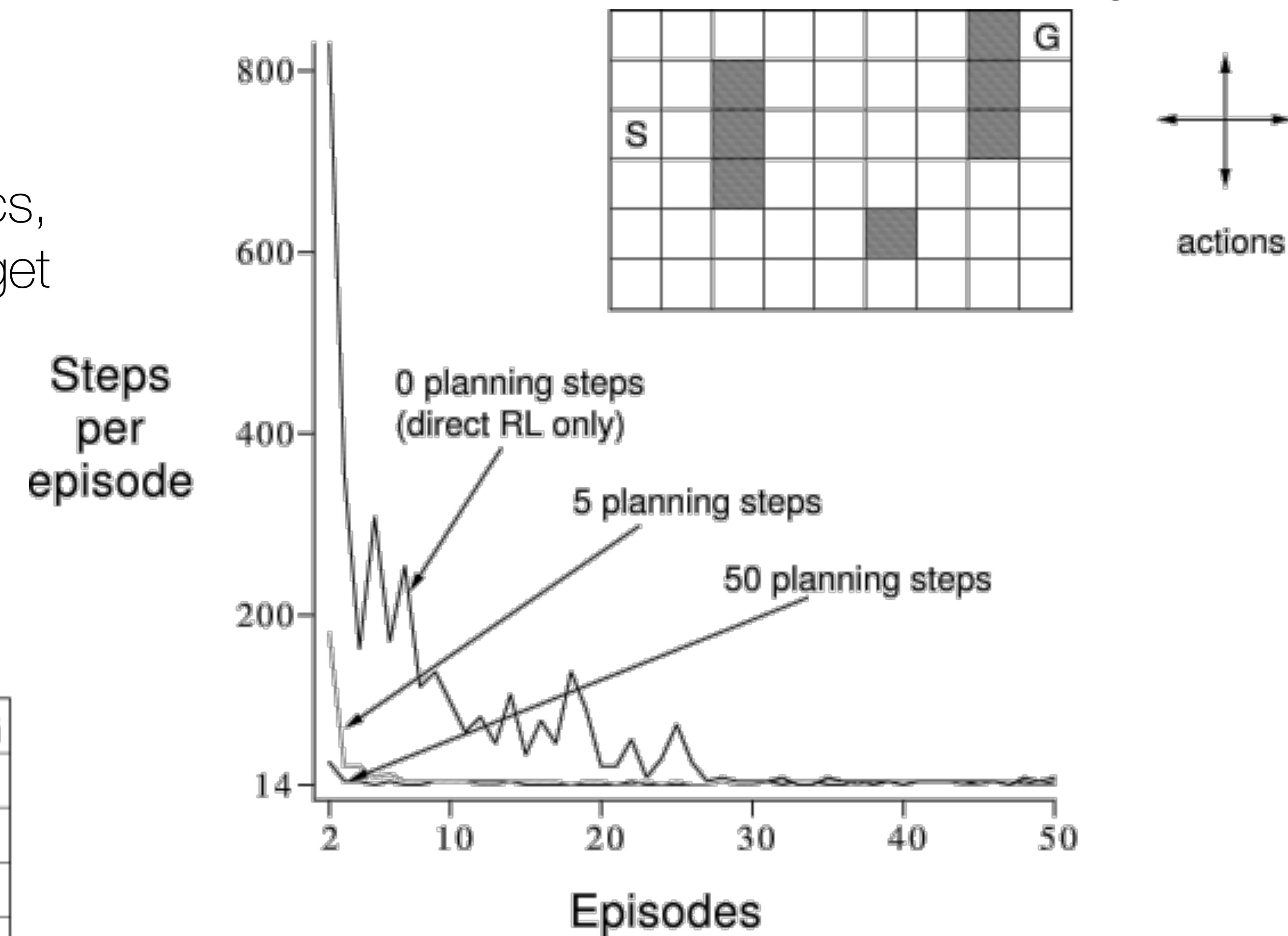


WITH PLANNING ($N=50$)



Sutton & Barto Fig. 9.6

Sutton & Barto Fig. 9.5





David Ha



Jürgen
Schmid-
huber

Recurrent World Models Facilitate Policy Evolution

NIPS 2018
Oral Presentation

Thirty-Second Annual Conference on
Neural Information Processing Systems
Montréal, Canada

Interactive demo. Tap screen or use arrow keys to override the agent's decisions.



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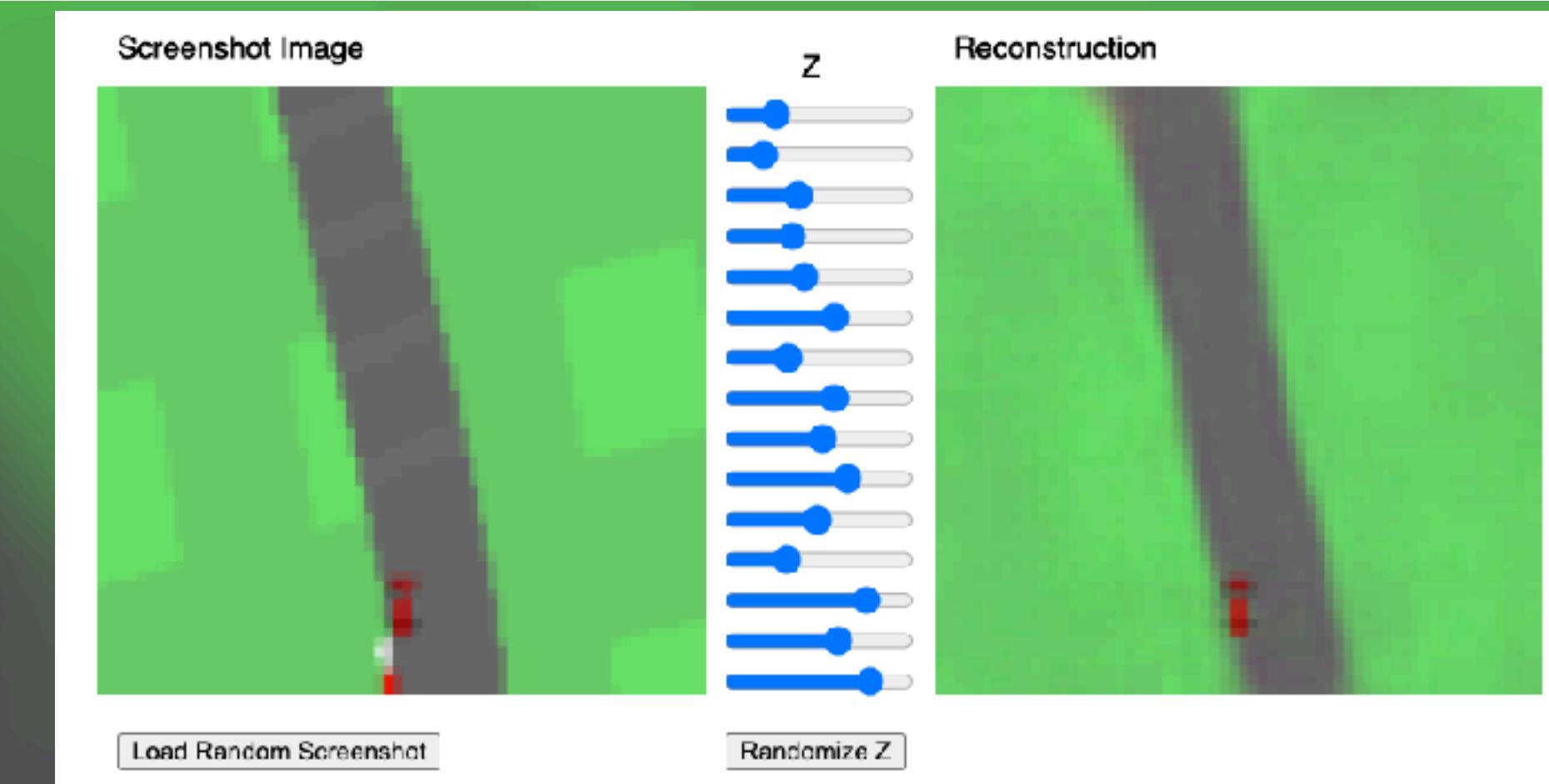


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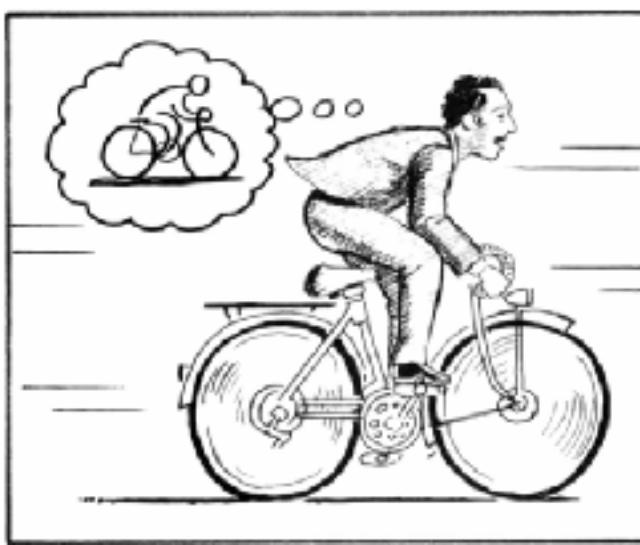
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Check out worldmodels.github.io/ for
interactive demos and more details!

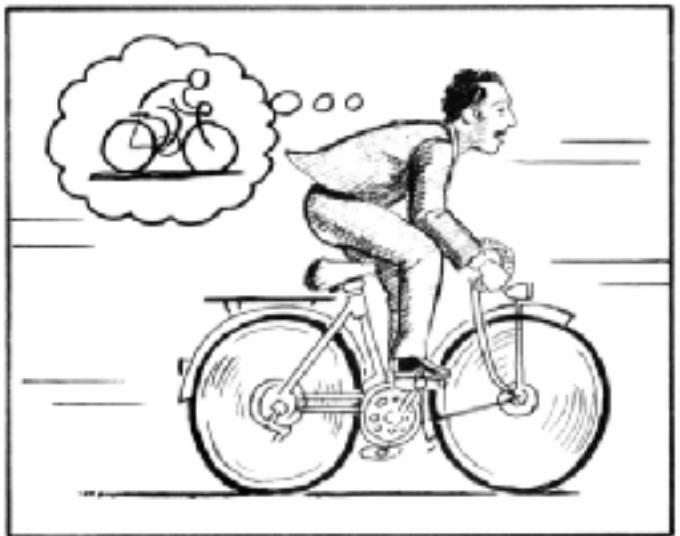
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World models

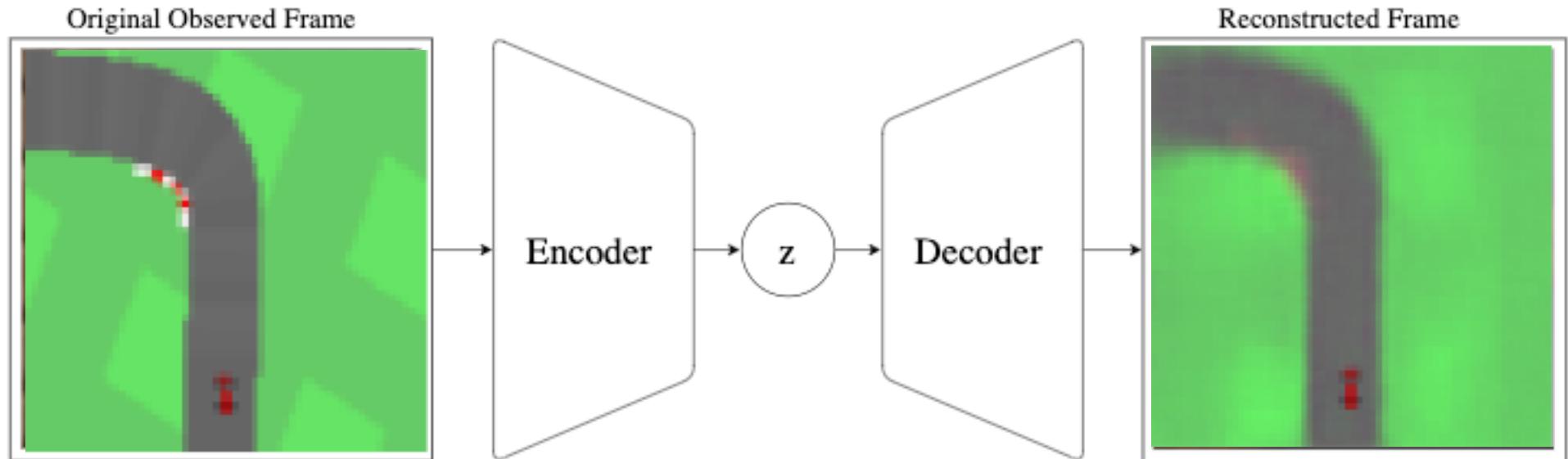


World models

- **Vision Model (M)** encodes high-dimensional visual data into a low-dimensional latent vector z

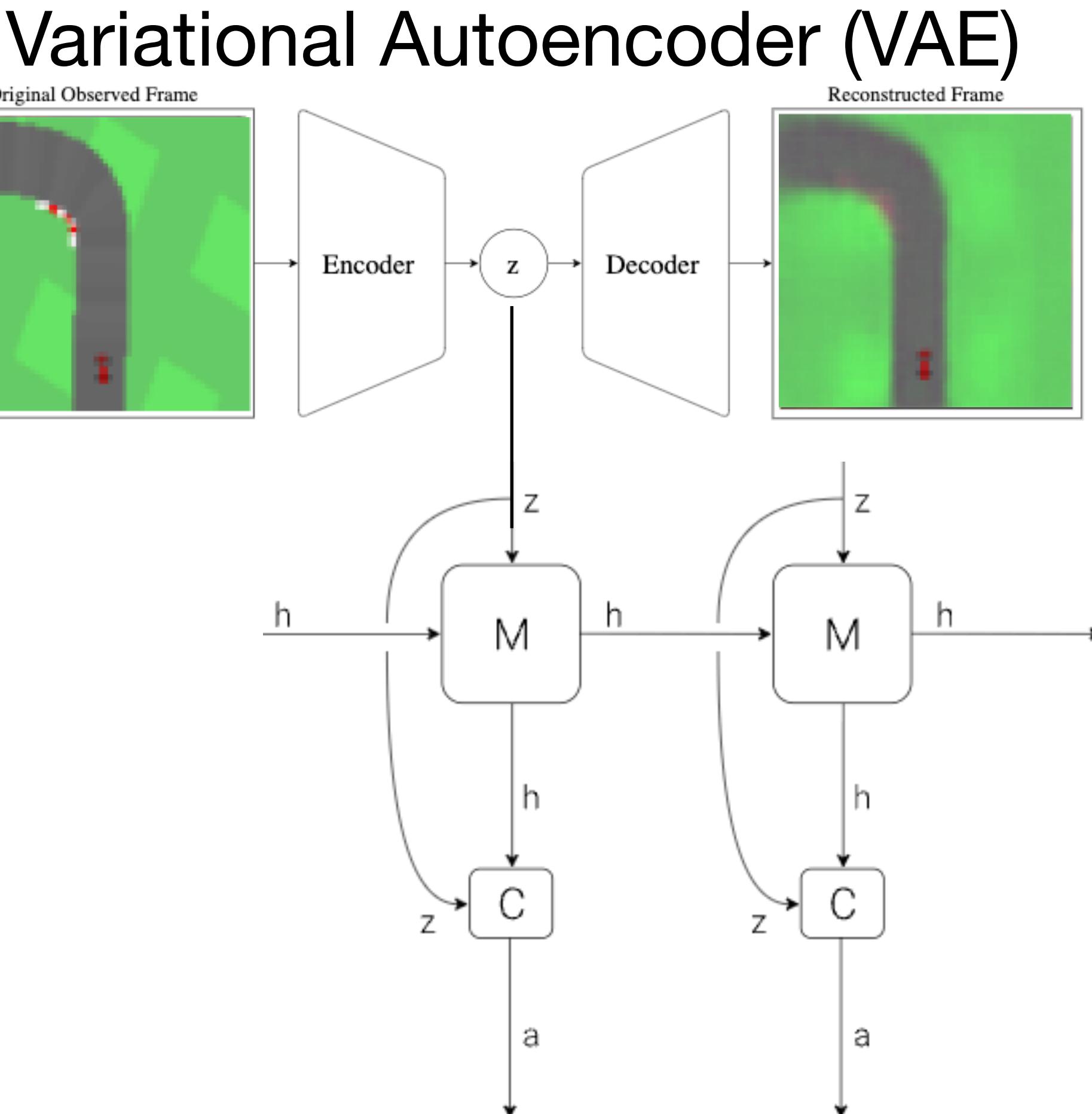
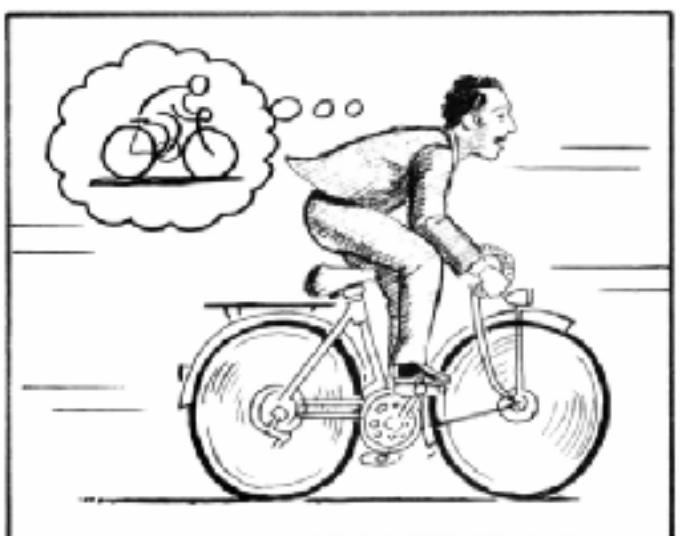


Variational Autoencoder (VAE)



World models

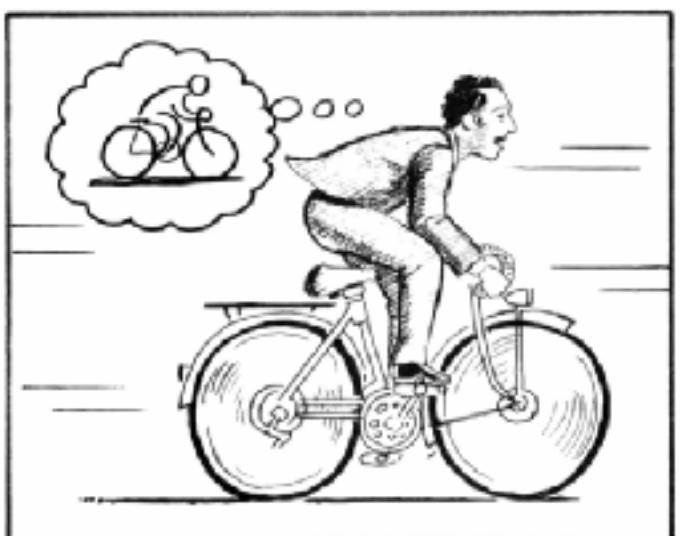
- **Vision Model (V)** encodes high-dimensional visual data into a low-dimensional latent vector z
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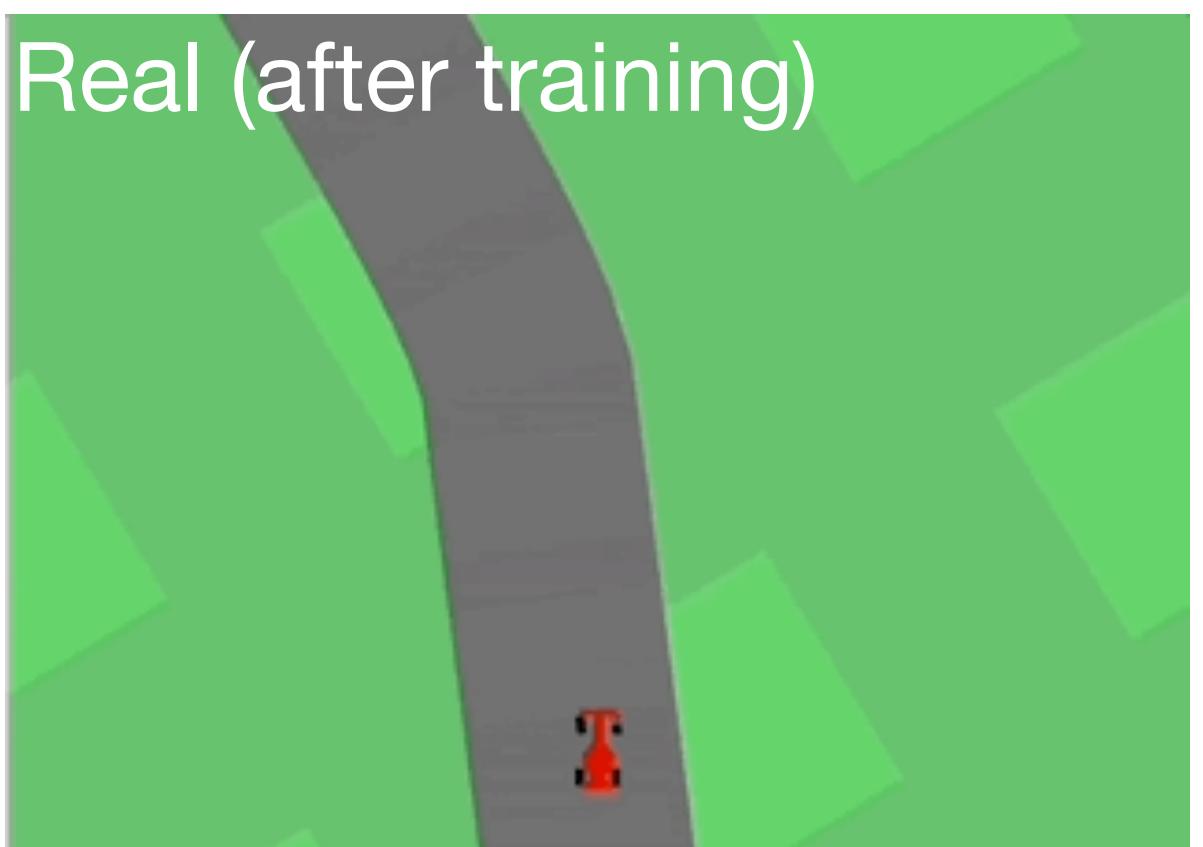
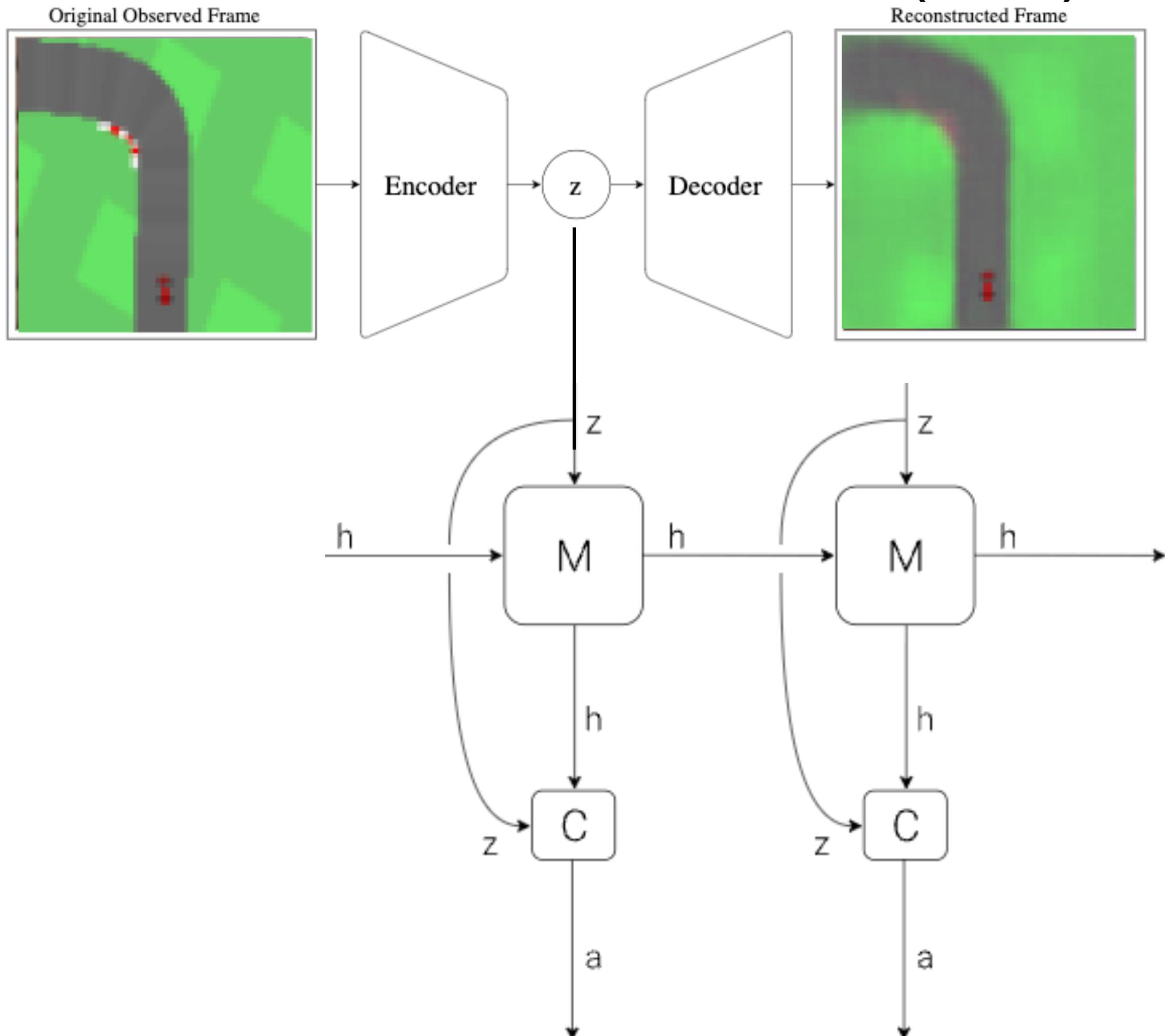
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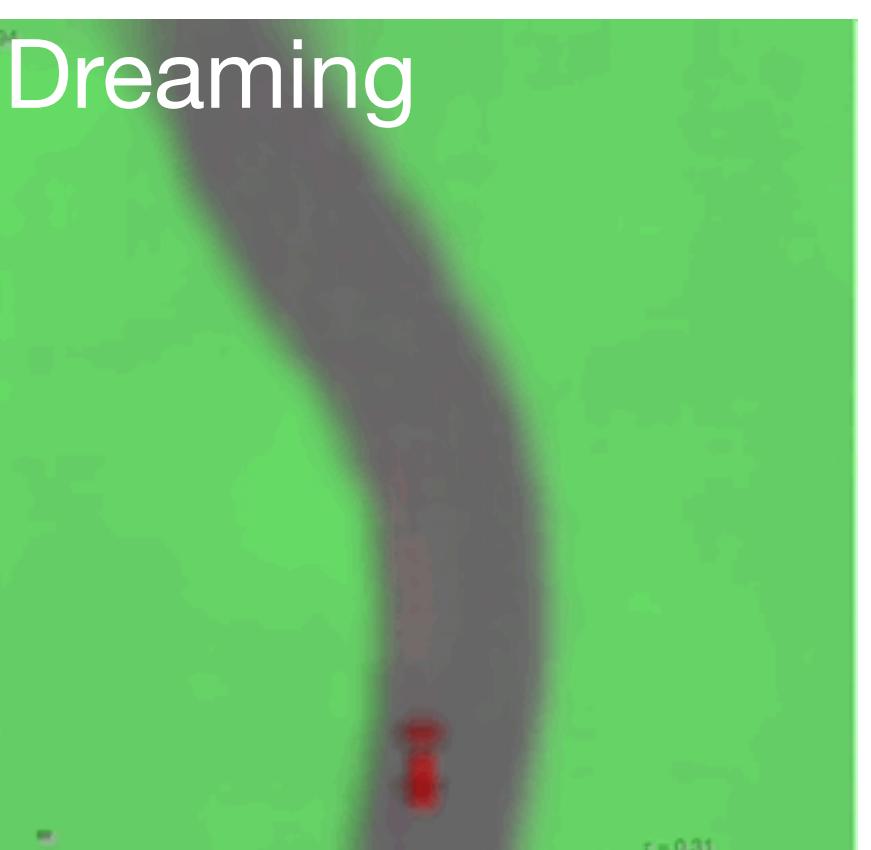
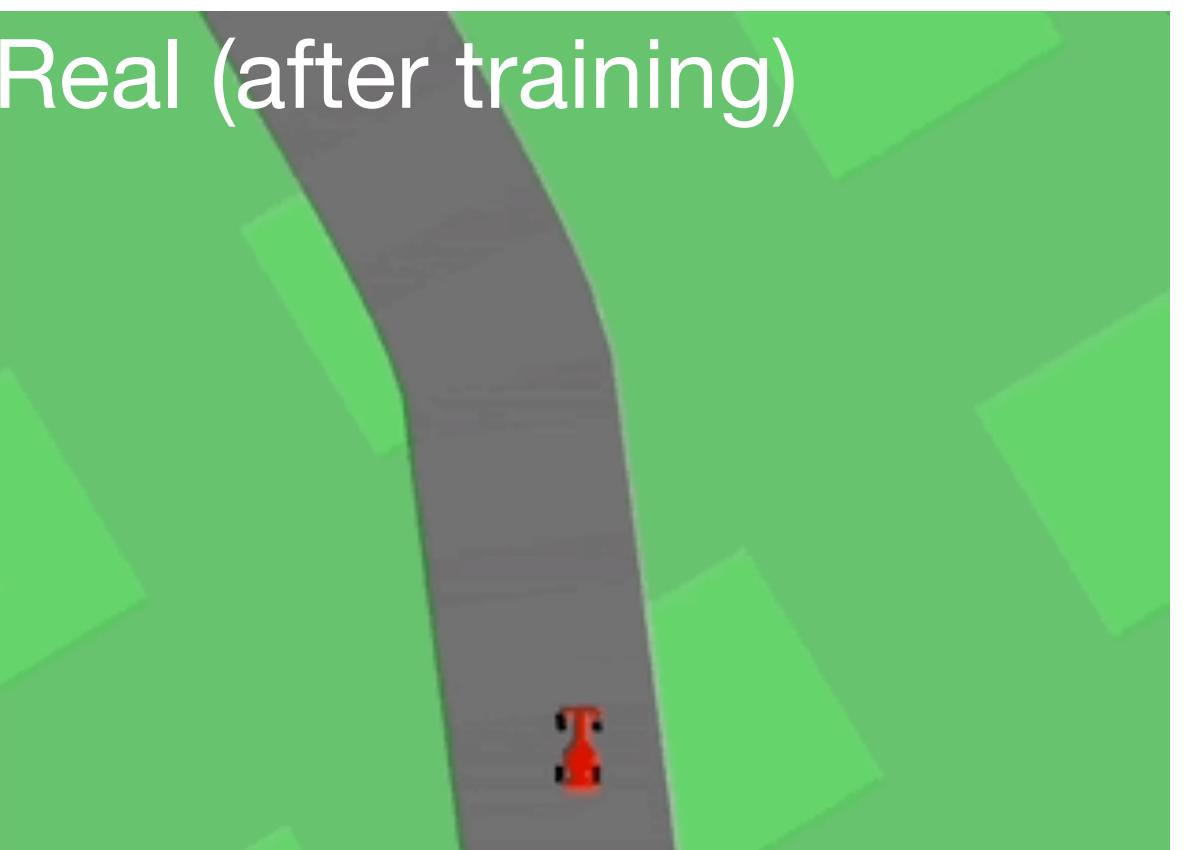
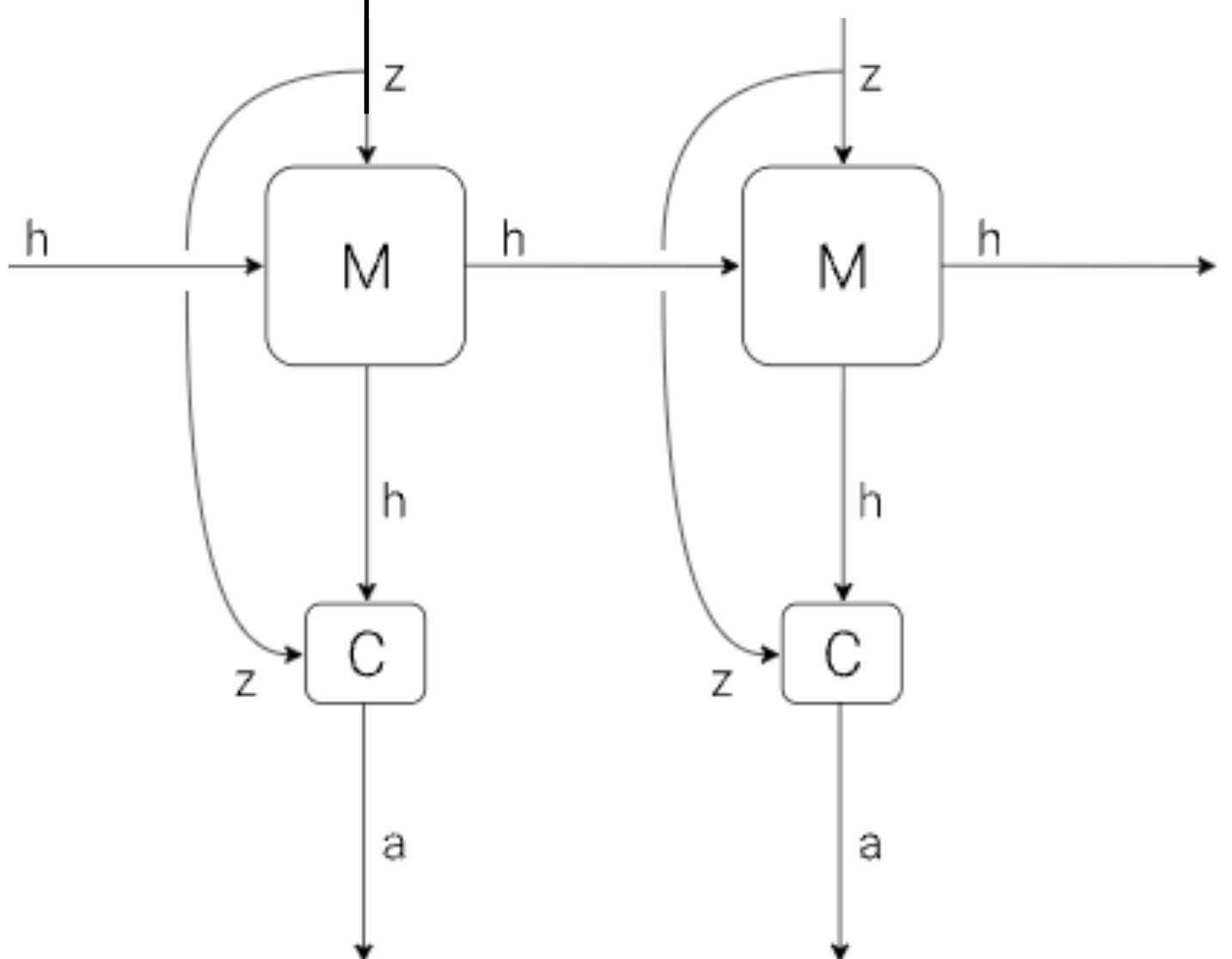
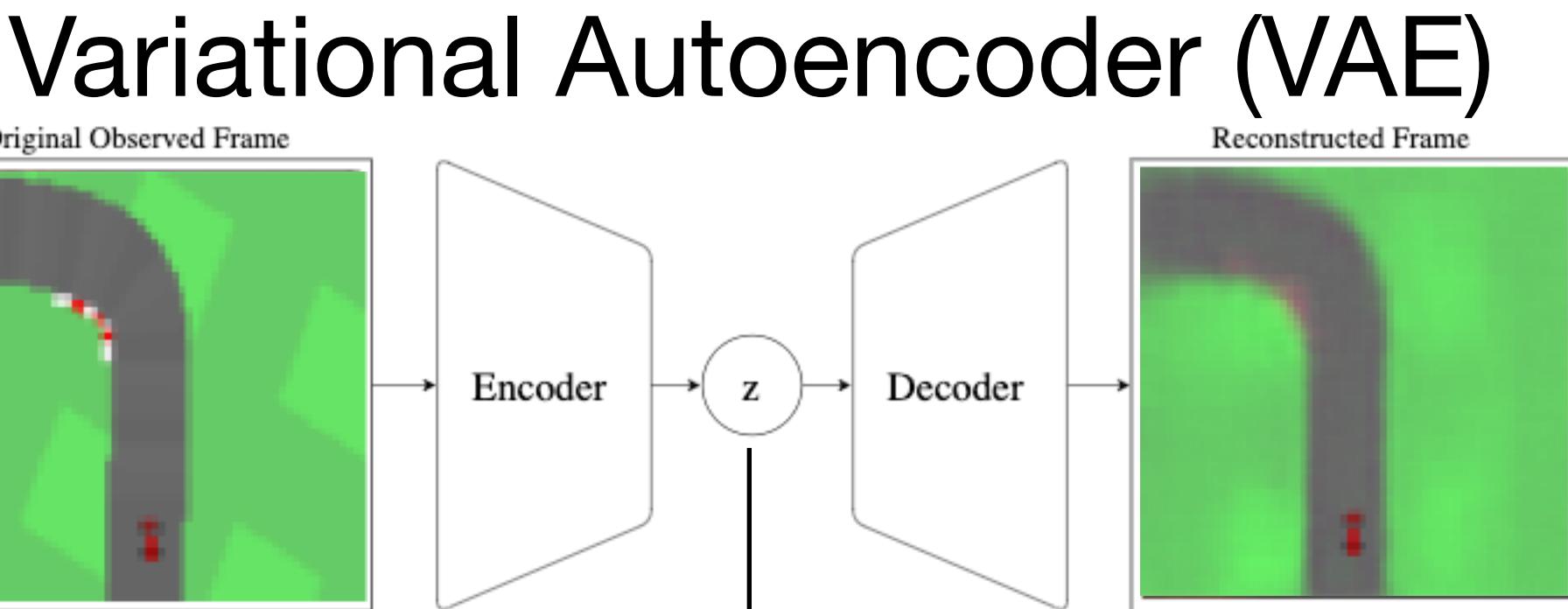
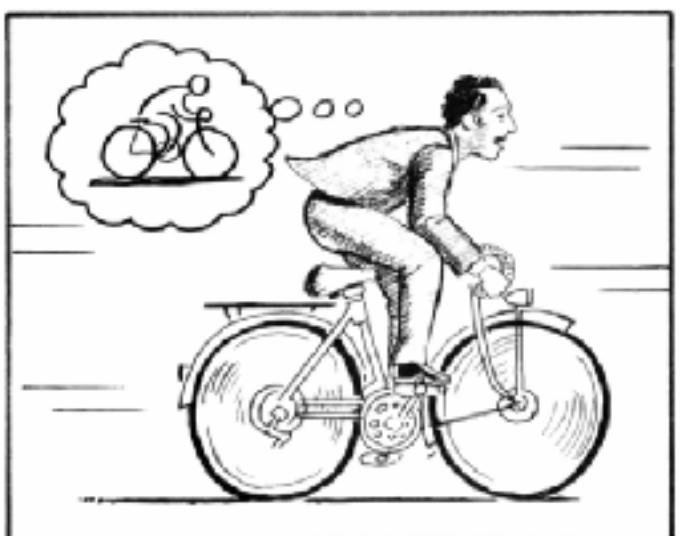
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- Training on dreams by simulating future states and treating them as real
 - Used to update controller weights



DreamerV3

Hafner et al., (2023)

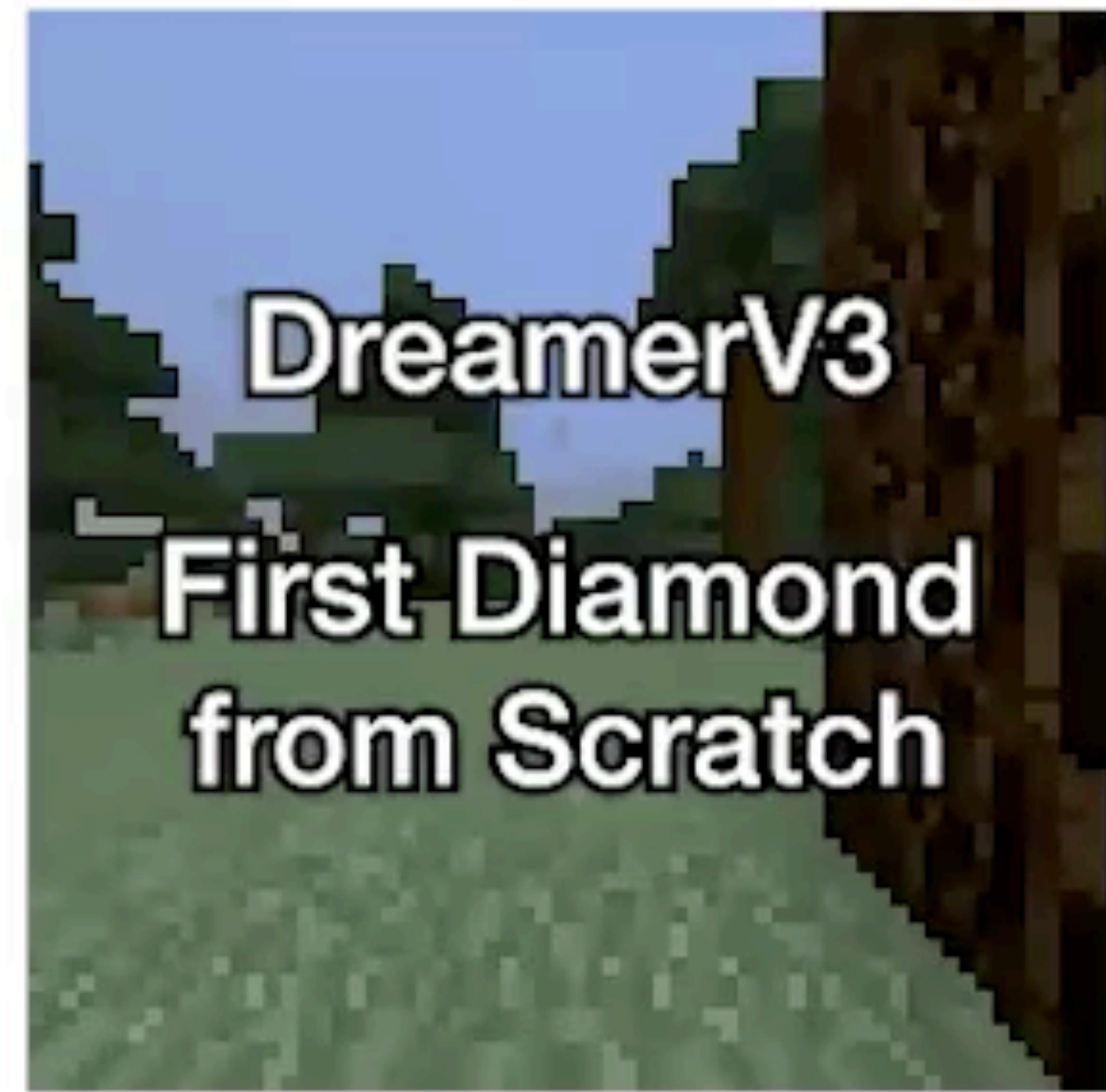
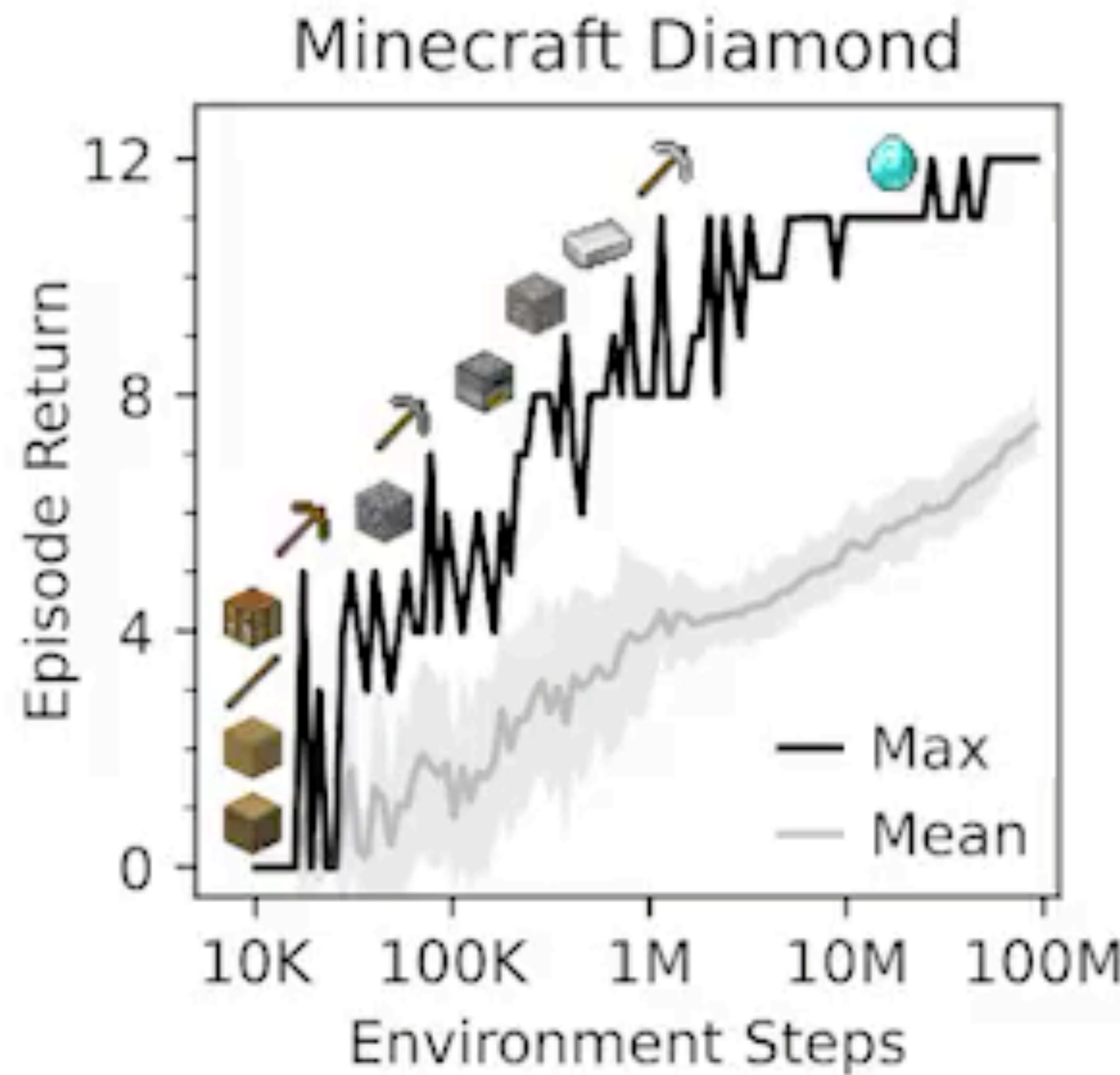


DreamerV3

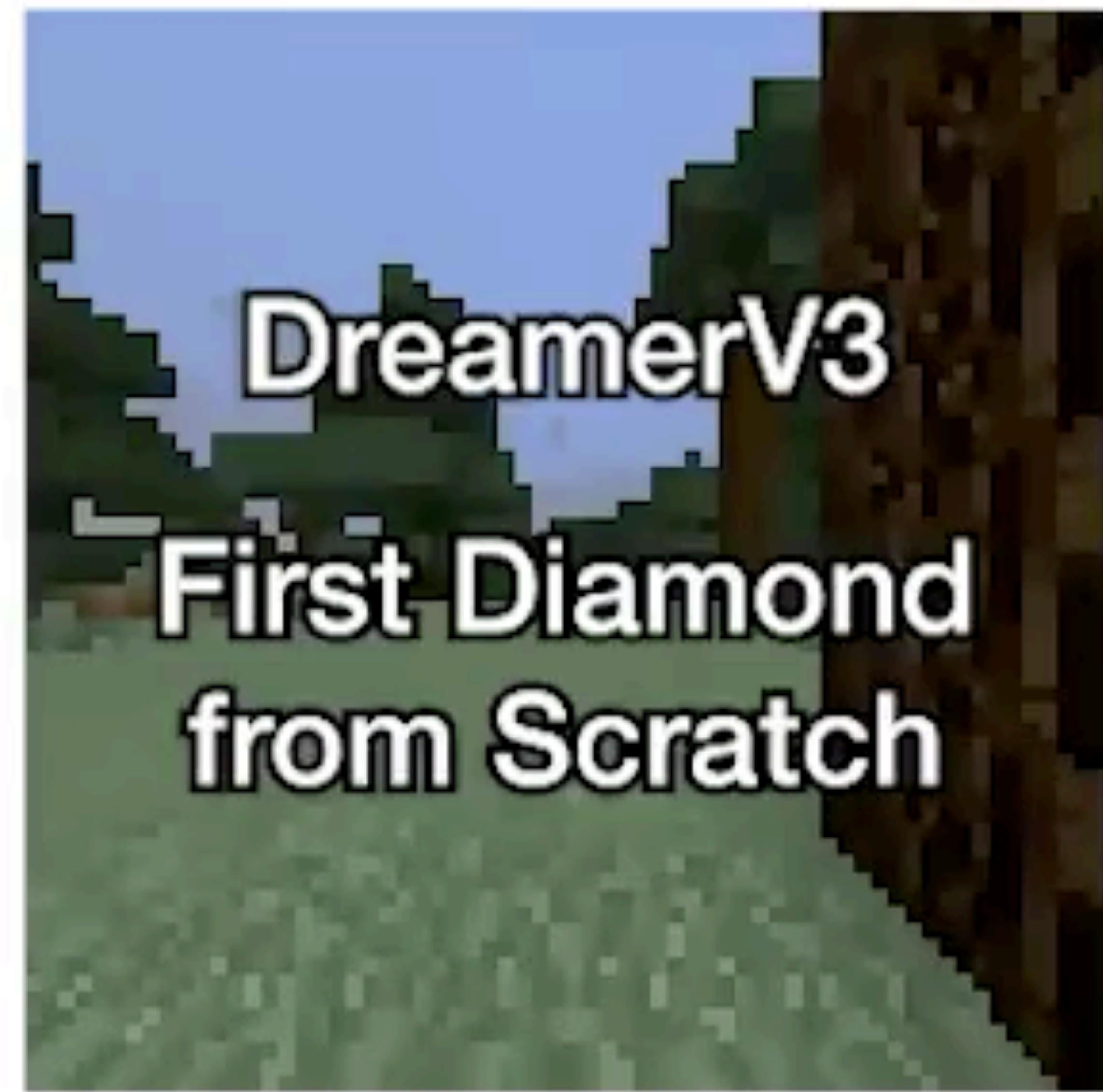
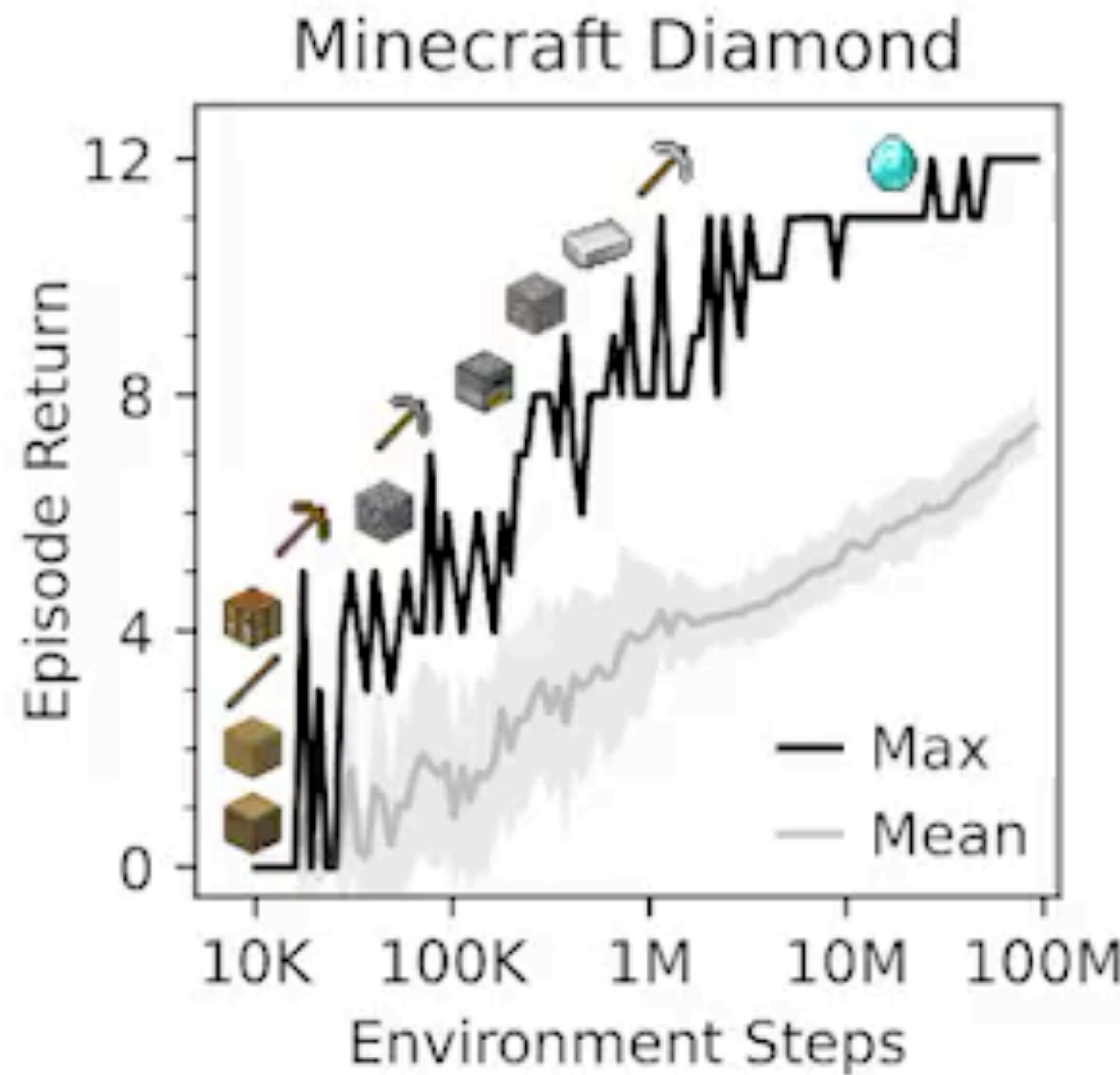
Hafner et al., (2023)



First algorithm to collect diamonds in Minecraft without human data or training curricula



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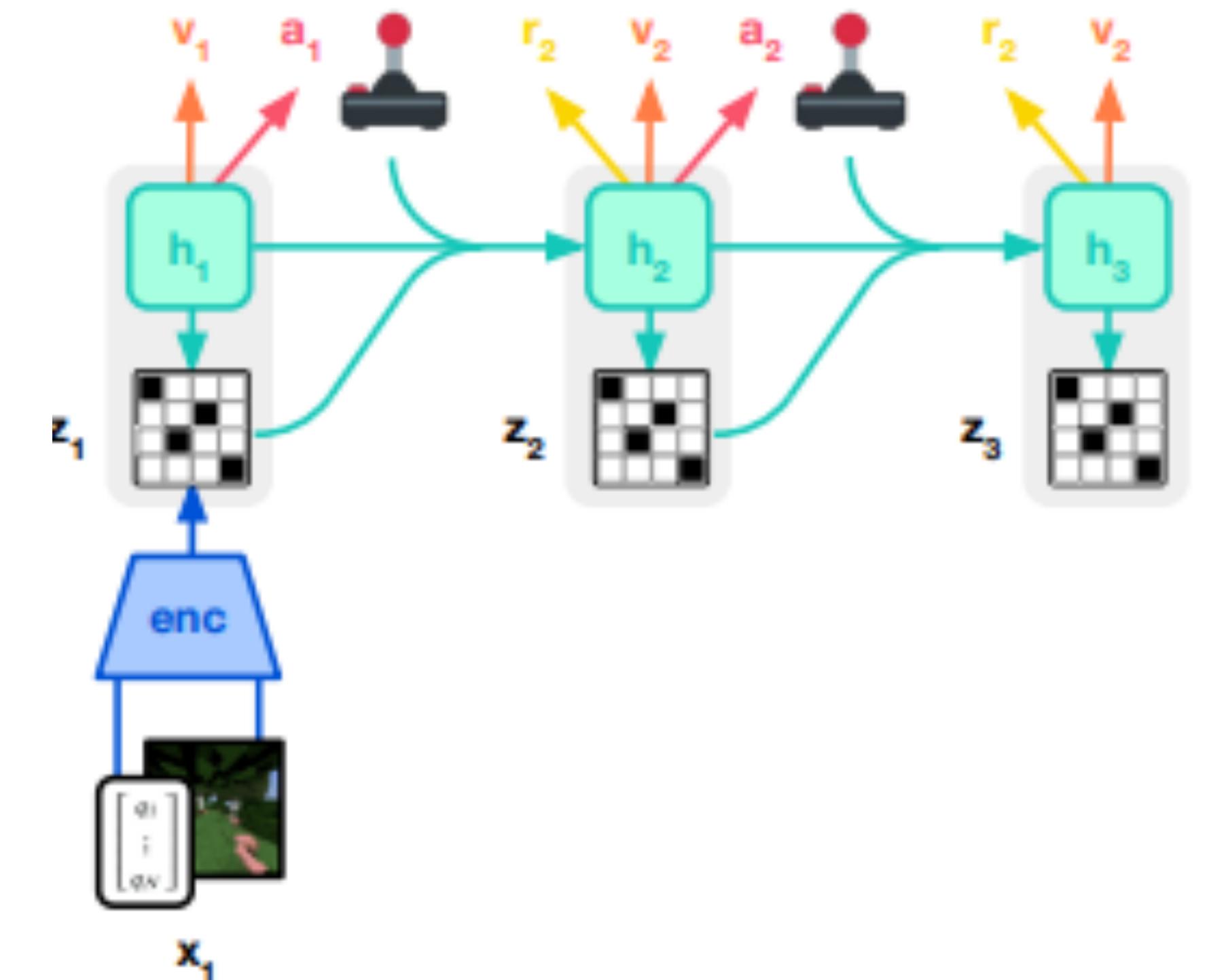
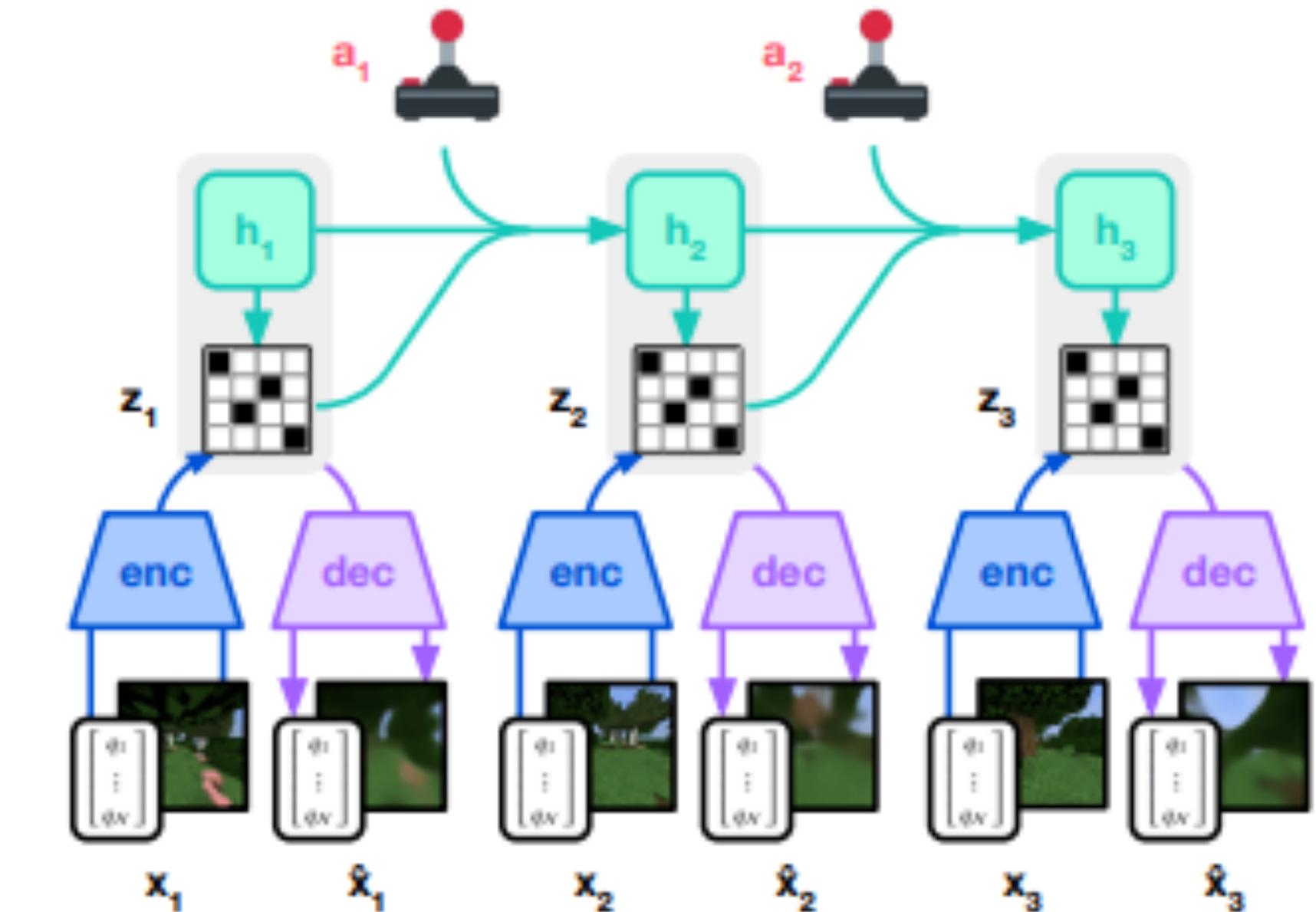
Dreamer Hafner et al., (2023)

Similar concept to World Models

- **Encoder** $z_t \sim q_\phi(z_t | h_t, x_t)$ given hidden state h_t and observations x_t
- **Sequence model** $h_{t+1} = f_\phi(h_t, z_t, a_t)$ and **dynamics predictor** $\hat{z}_t \sim p_\phi(\hat{z}_t | h_t)$

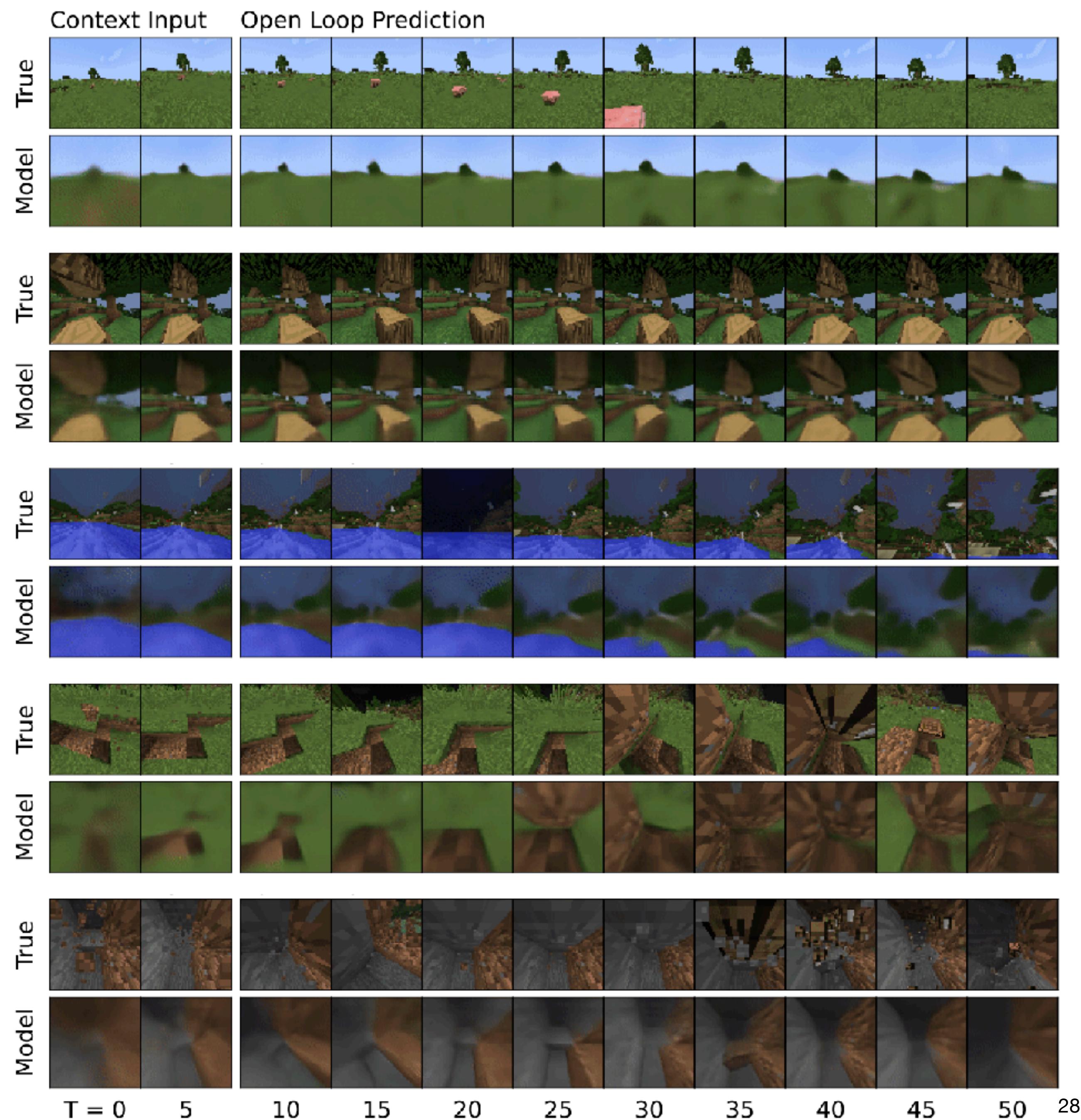
Actor-critic architecture

- **Actor** $a_t \sim \pi_\theta(a_t | s_t)$ where $s_t = \{h_t, z_t\}$
- **Critic** $v_\psi(R_t | s_t)$



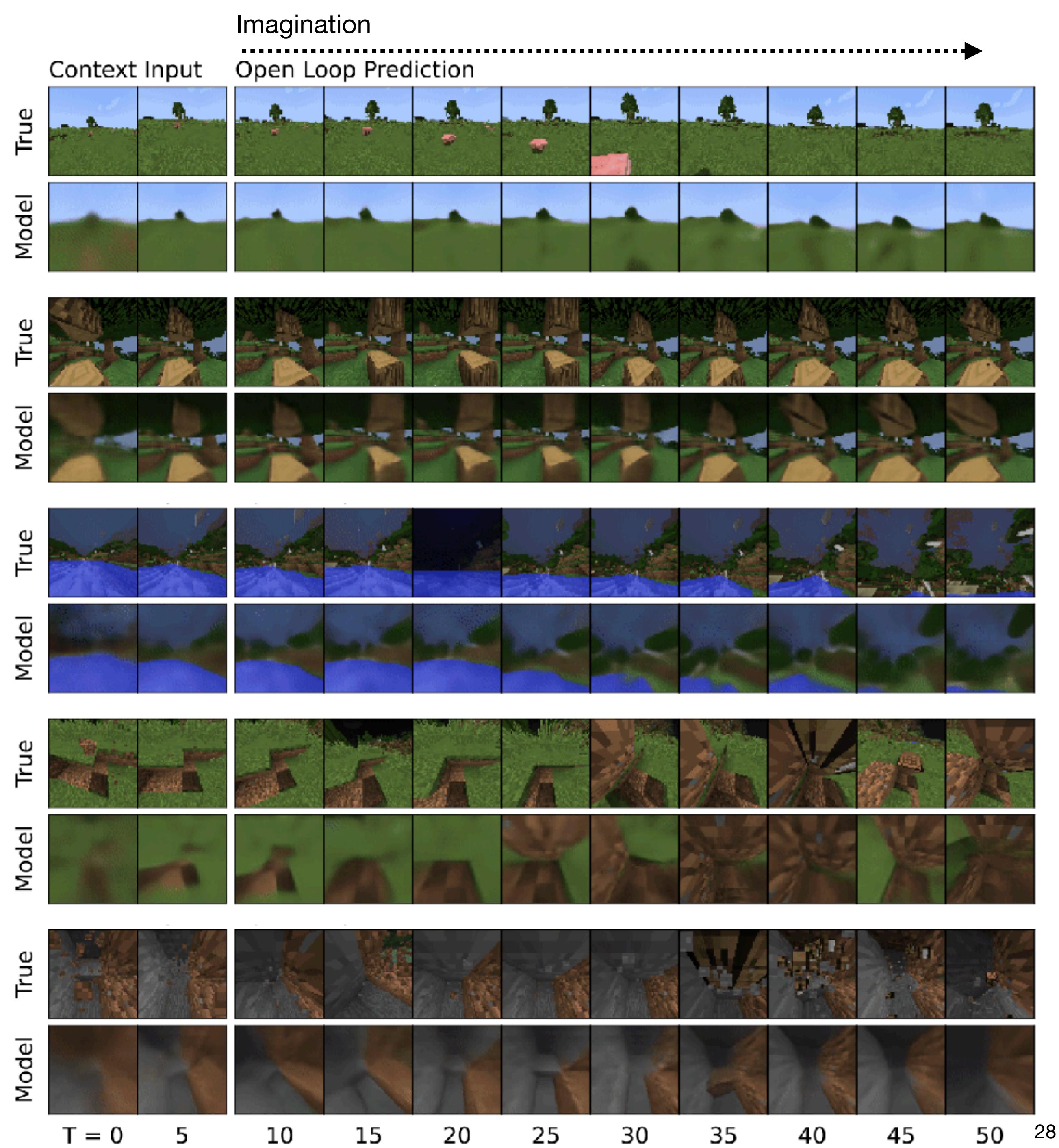
Model-based planning via simulating the future

- Main purpose of the model is to supplement real training experiences (direct RL) by simulating (imagining) future experiences



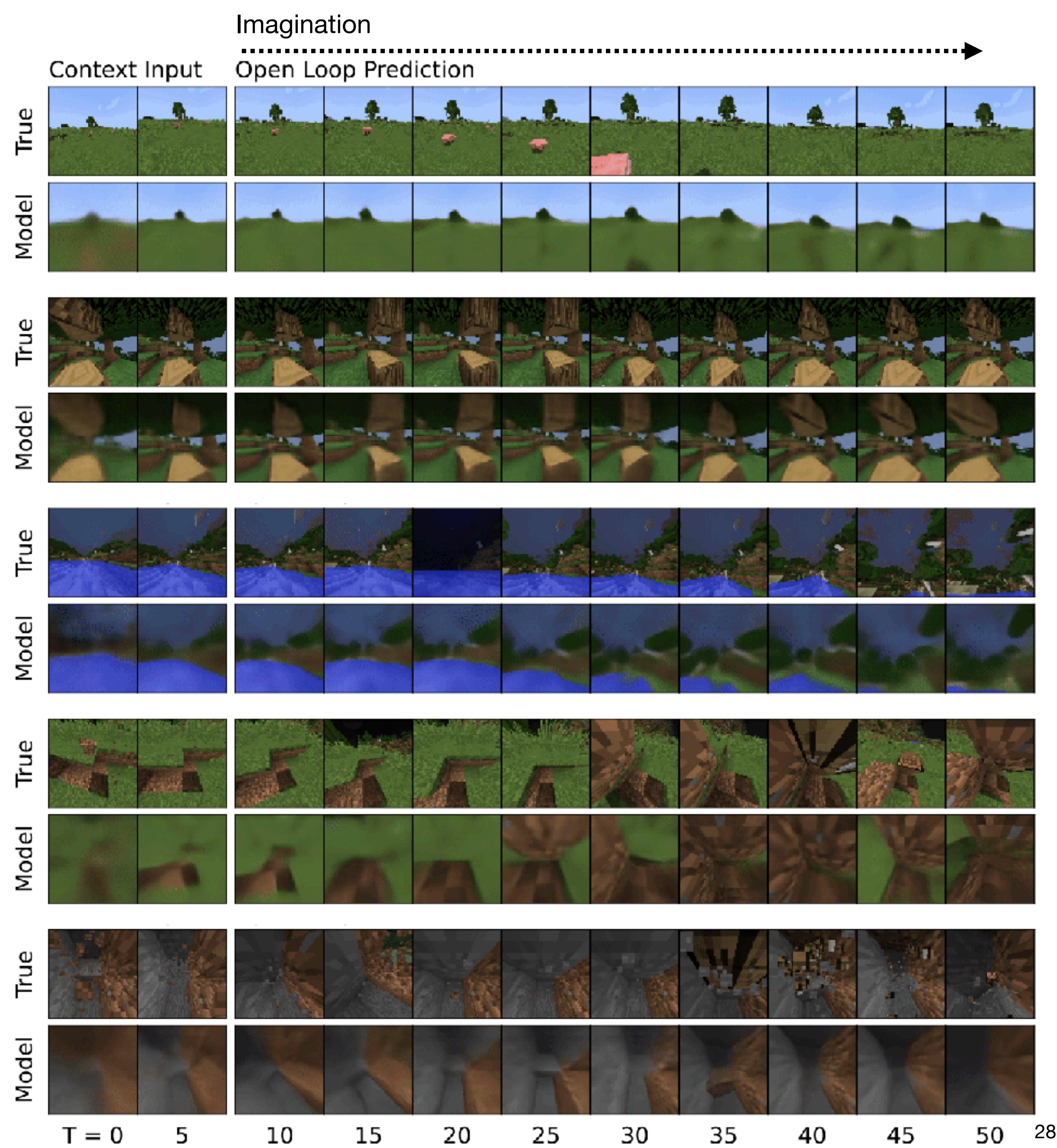
Model-based planning via simulating the future

- Main purpose of the model is to supplement real training experiences (direct RL) by simulating (imagining) future experiences



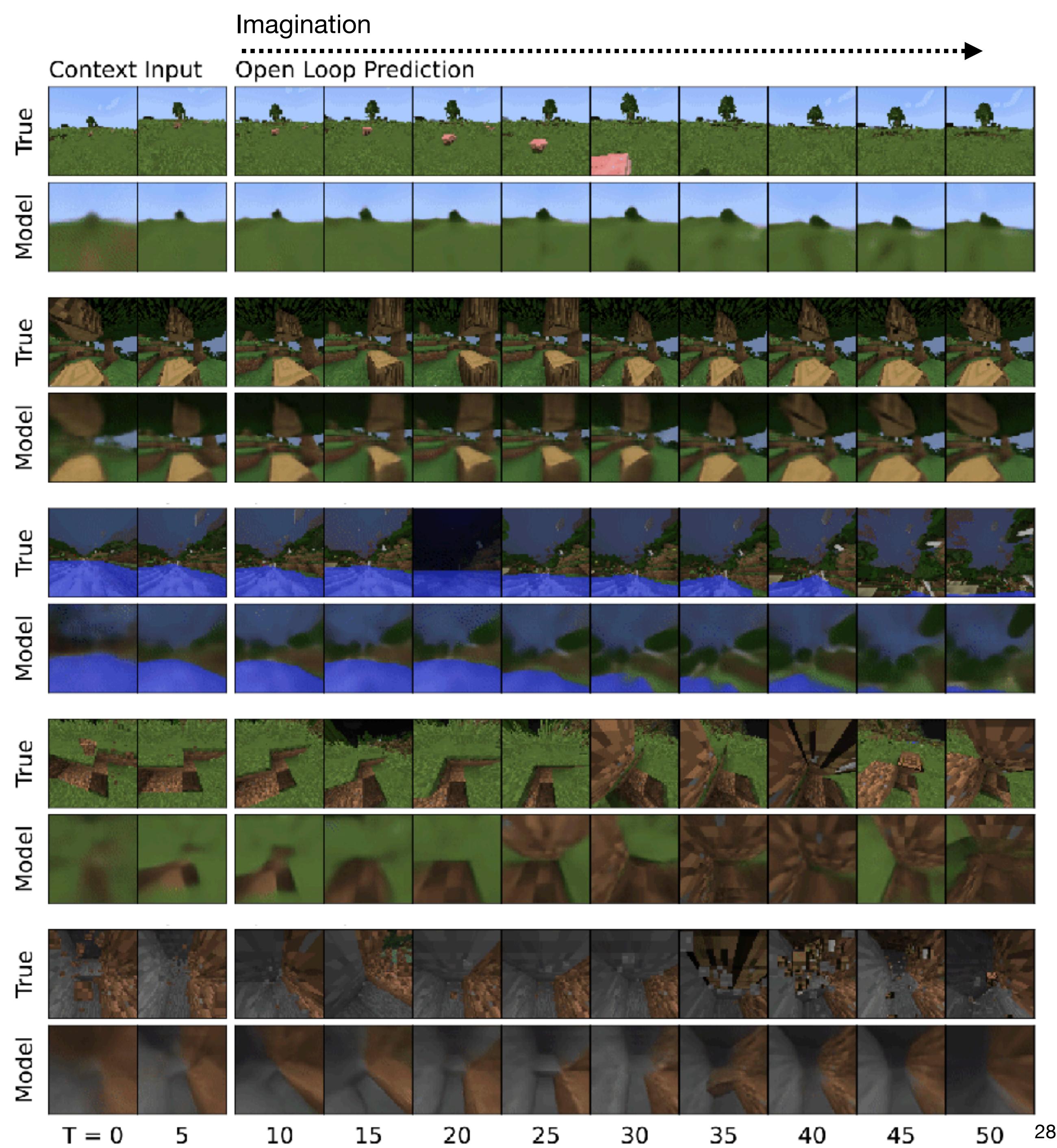
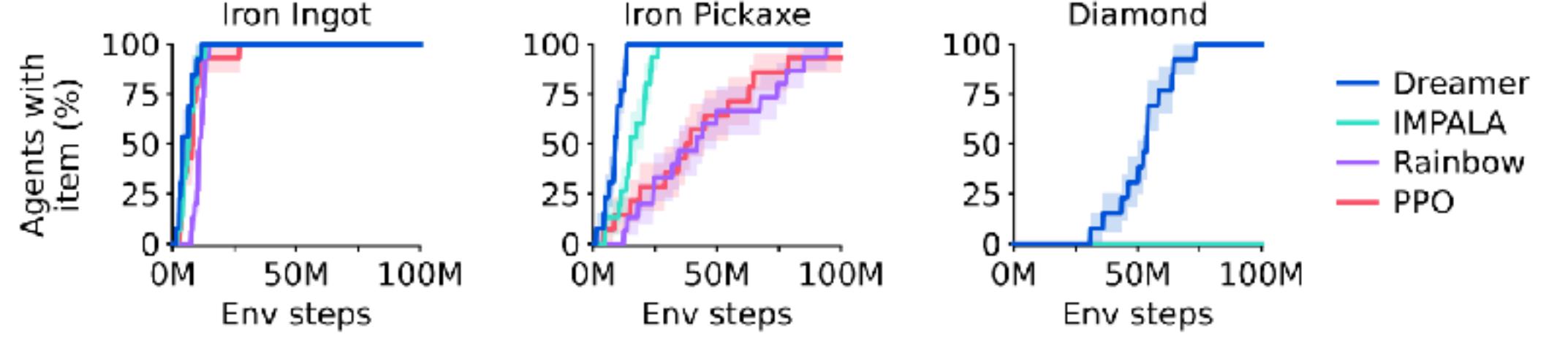
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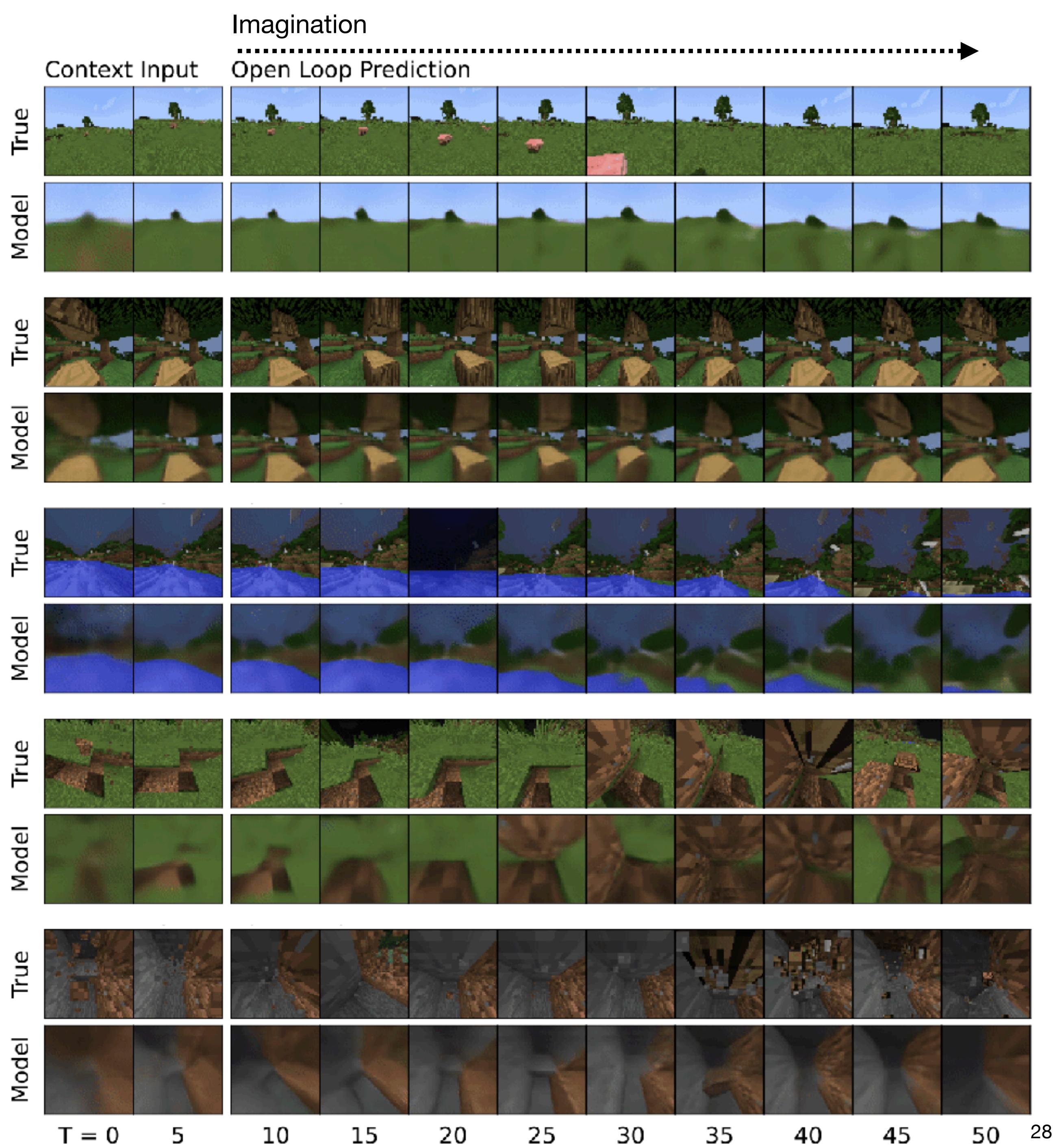
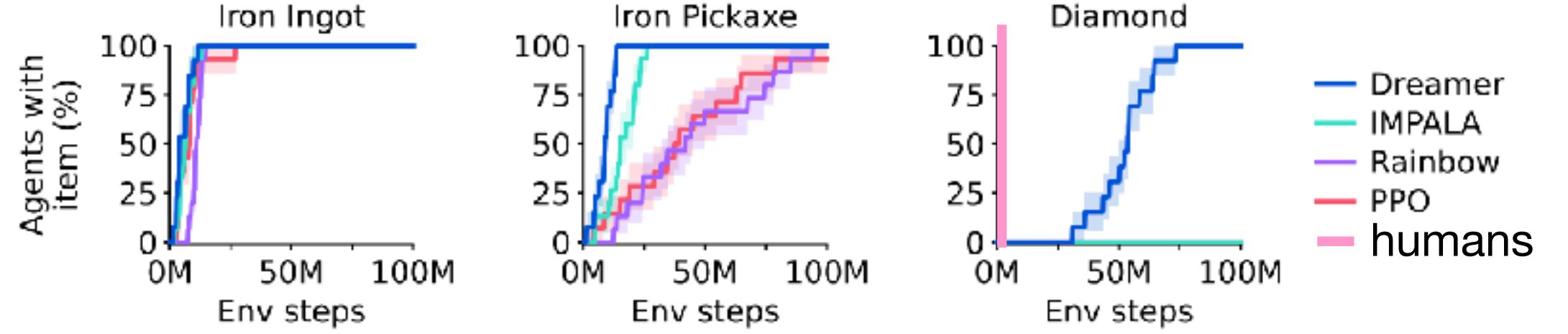
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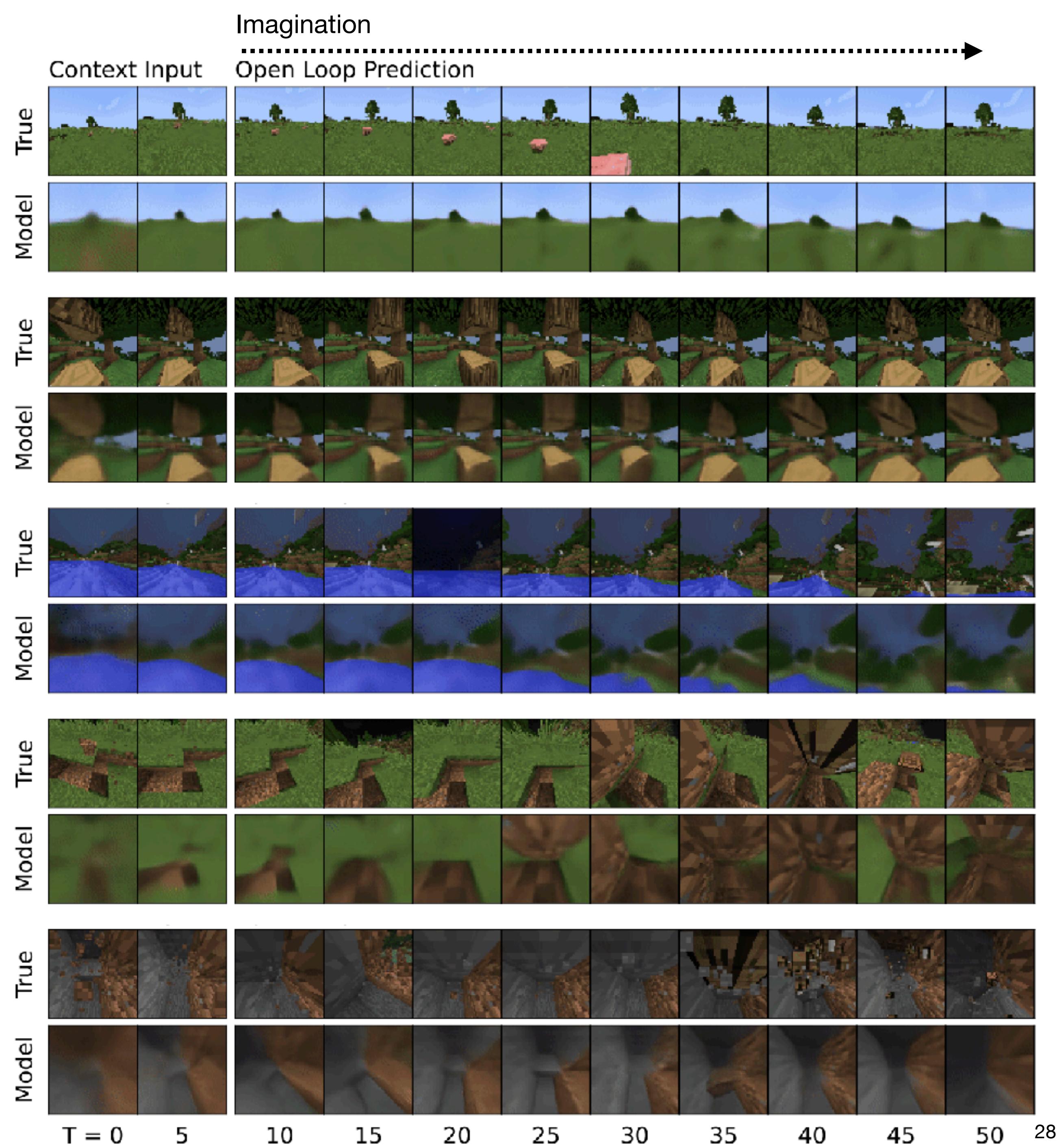
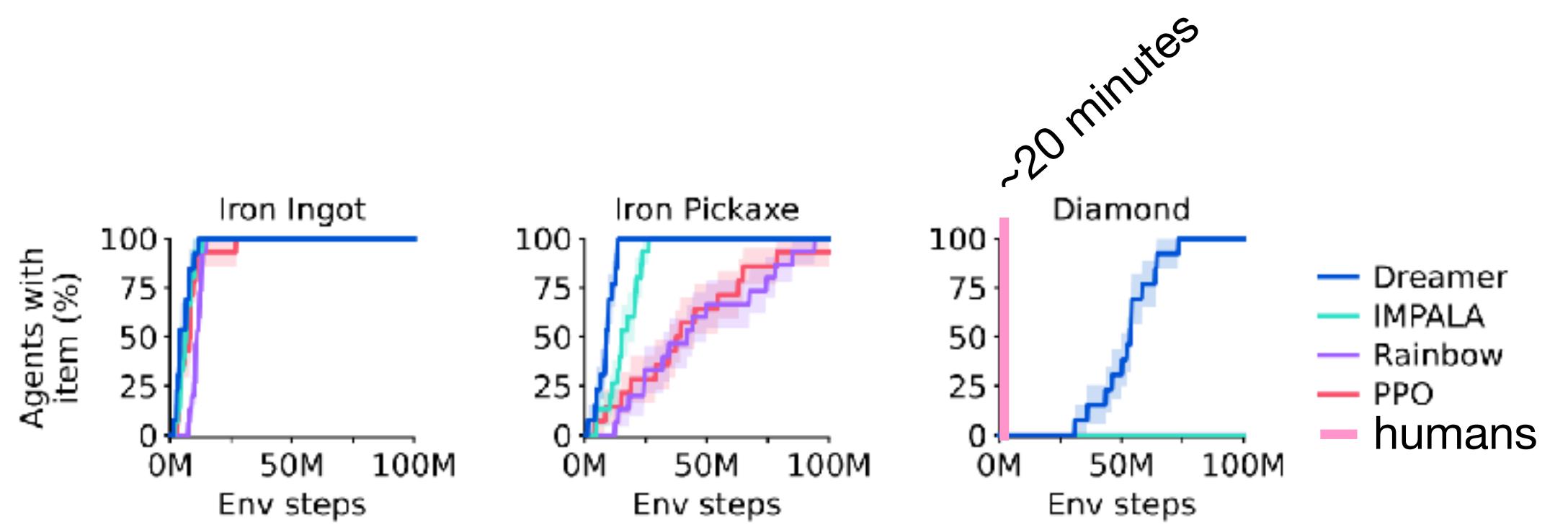
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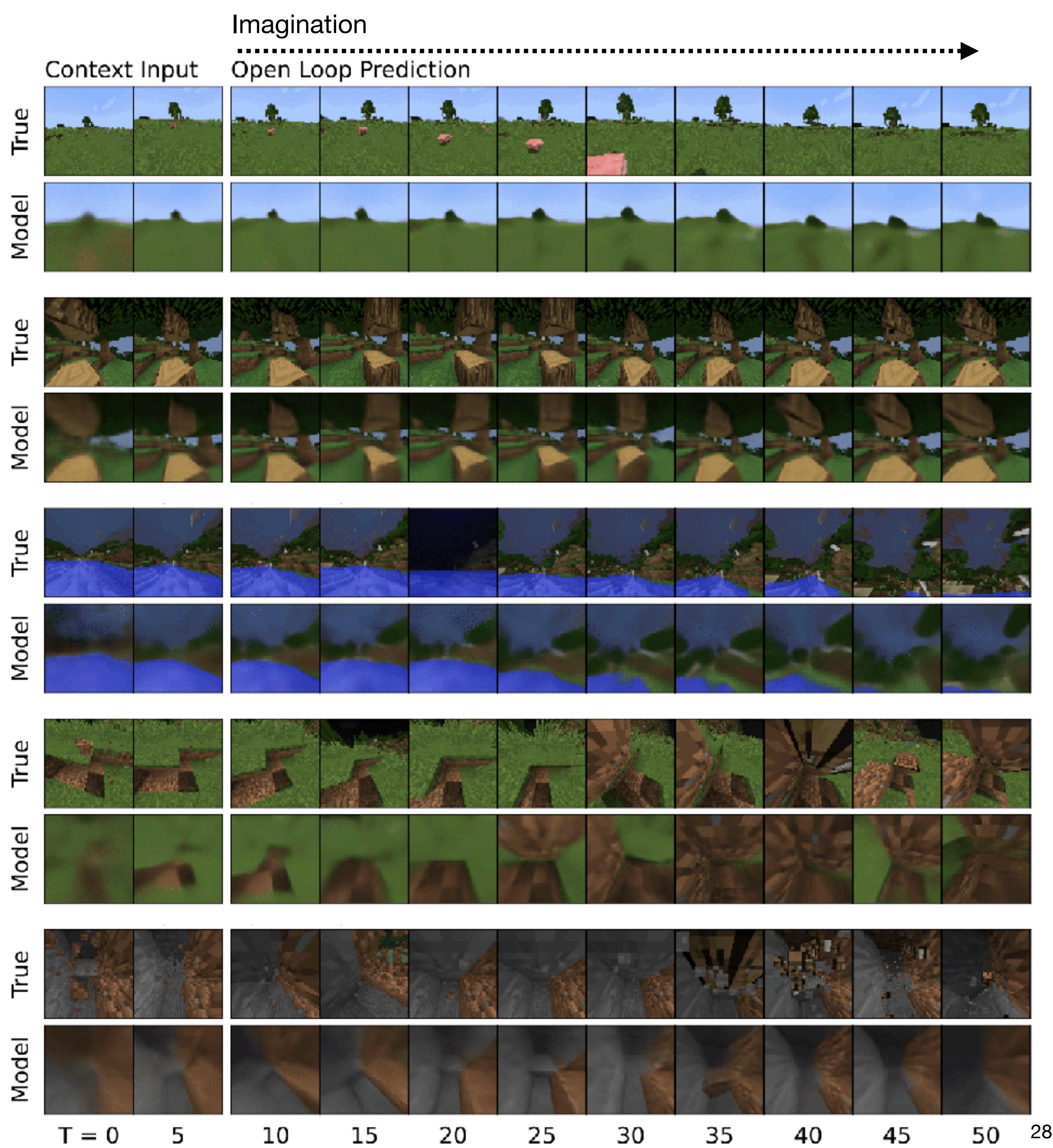
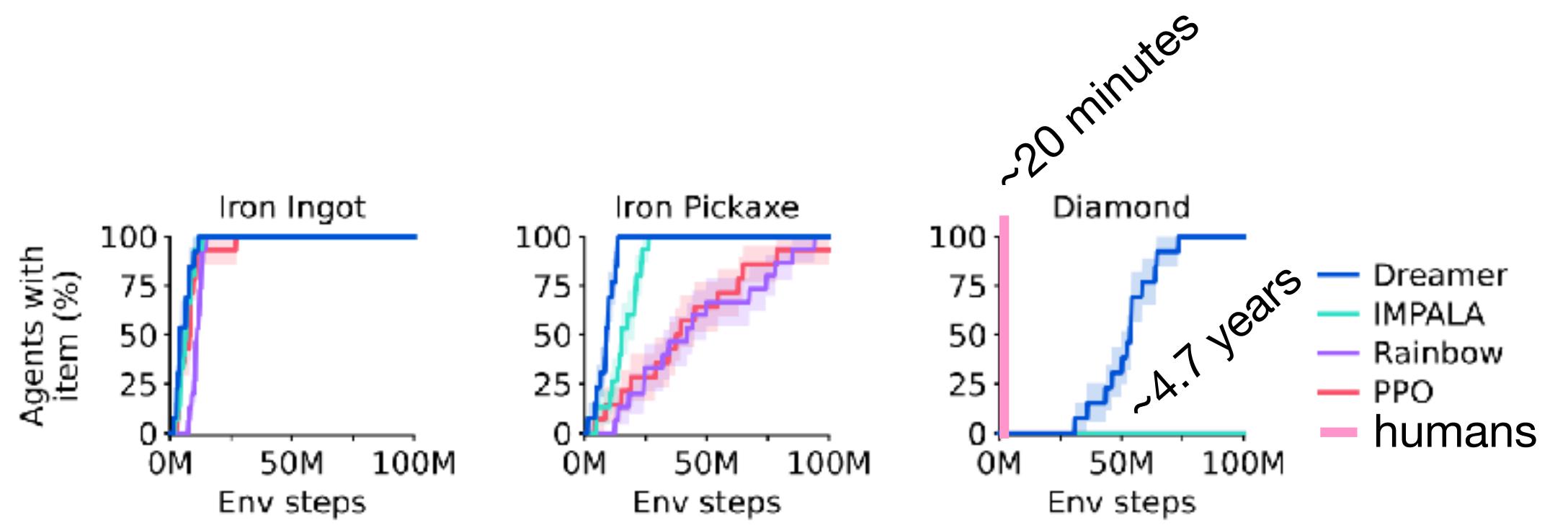
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Model-based methods summary

How is the model learned?

- Through trial-and-error learning using delta-rule updates
- With modern ML techniques
 - Encode high-dimensional stimuli into a low-dimensional representation z
 - Learn the temporal dynamics $P(z_{t+1} | z_t)$

How is the model used?

- Use simulated experiences to augment direct RL (i.e., learning from real experiences)
- Model-free methods (e.g., actor-critic) can also be combined with model-based learning to great effect (Dreamer)

5 minute break

Balancing flexibility and efficiency

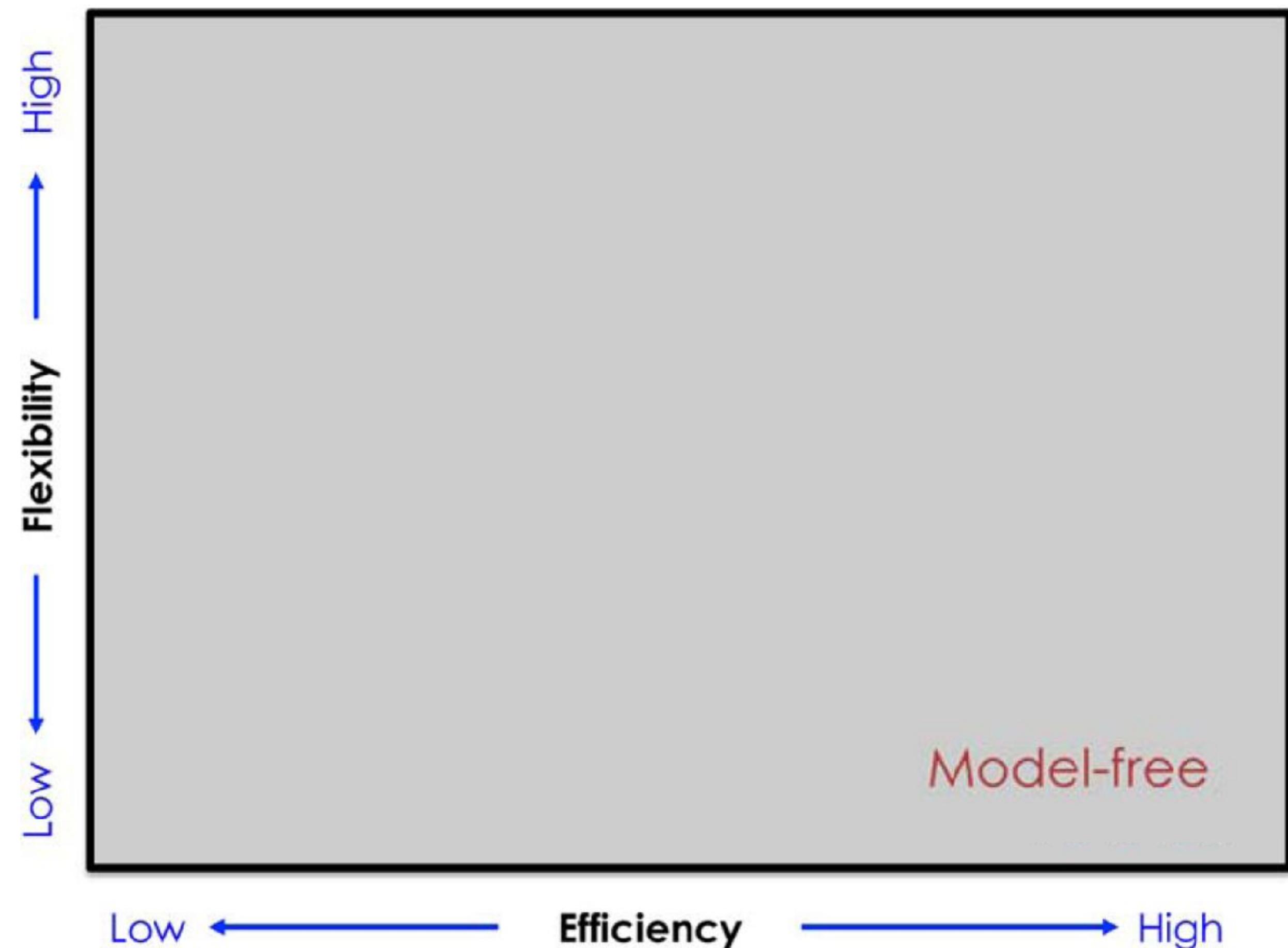
- Model-free methods are typically more data efficient (less training examples)
 - But lack flexibility to changes in the environment
- Model-based methods are highly flexible (local changes in environment lead to local changes in model)
 - But typically requires much more data to learn
- Is there nothing in between?



Gershman (2018)

Balancing flexibility and efficiency

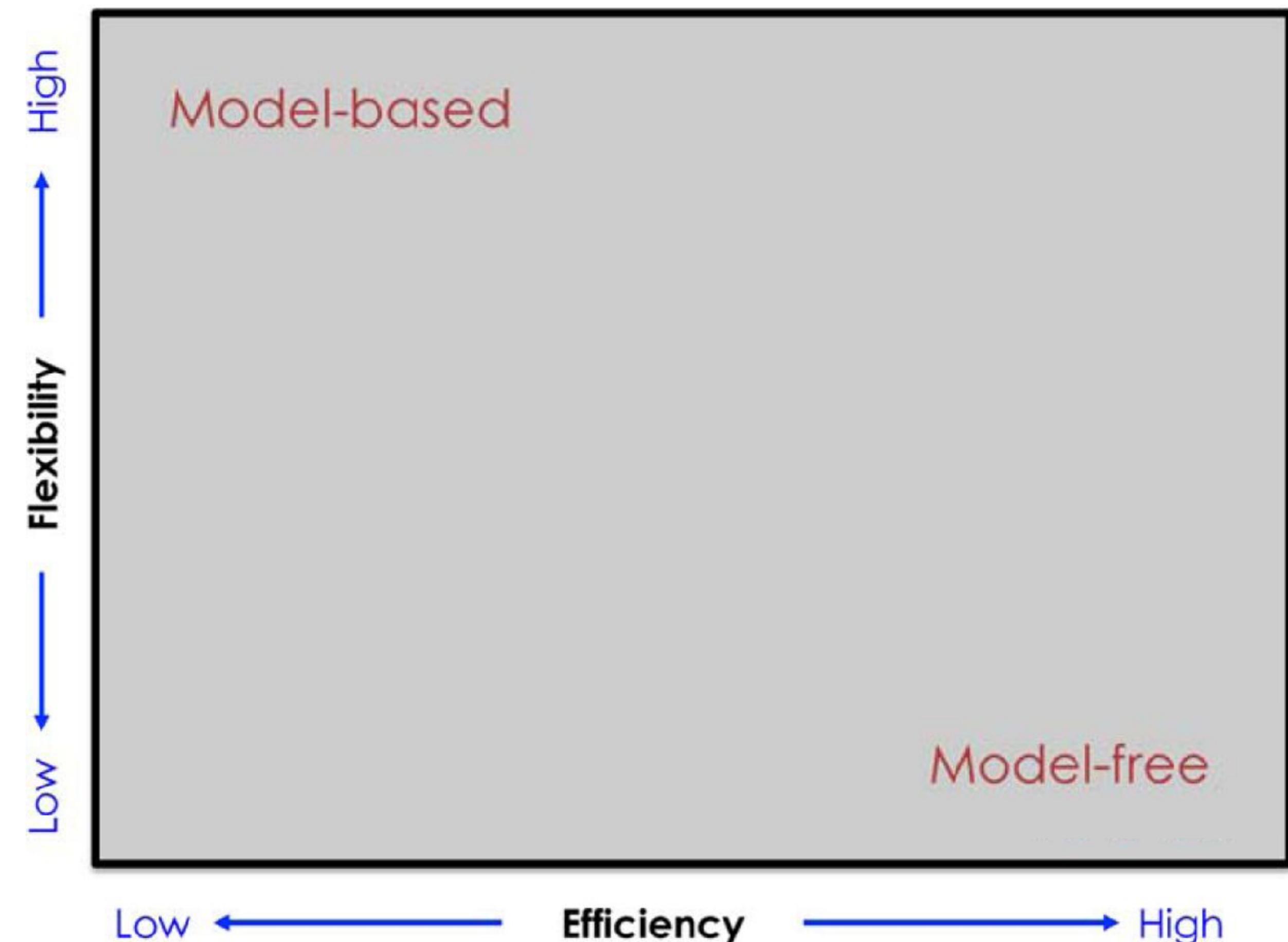
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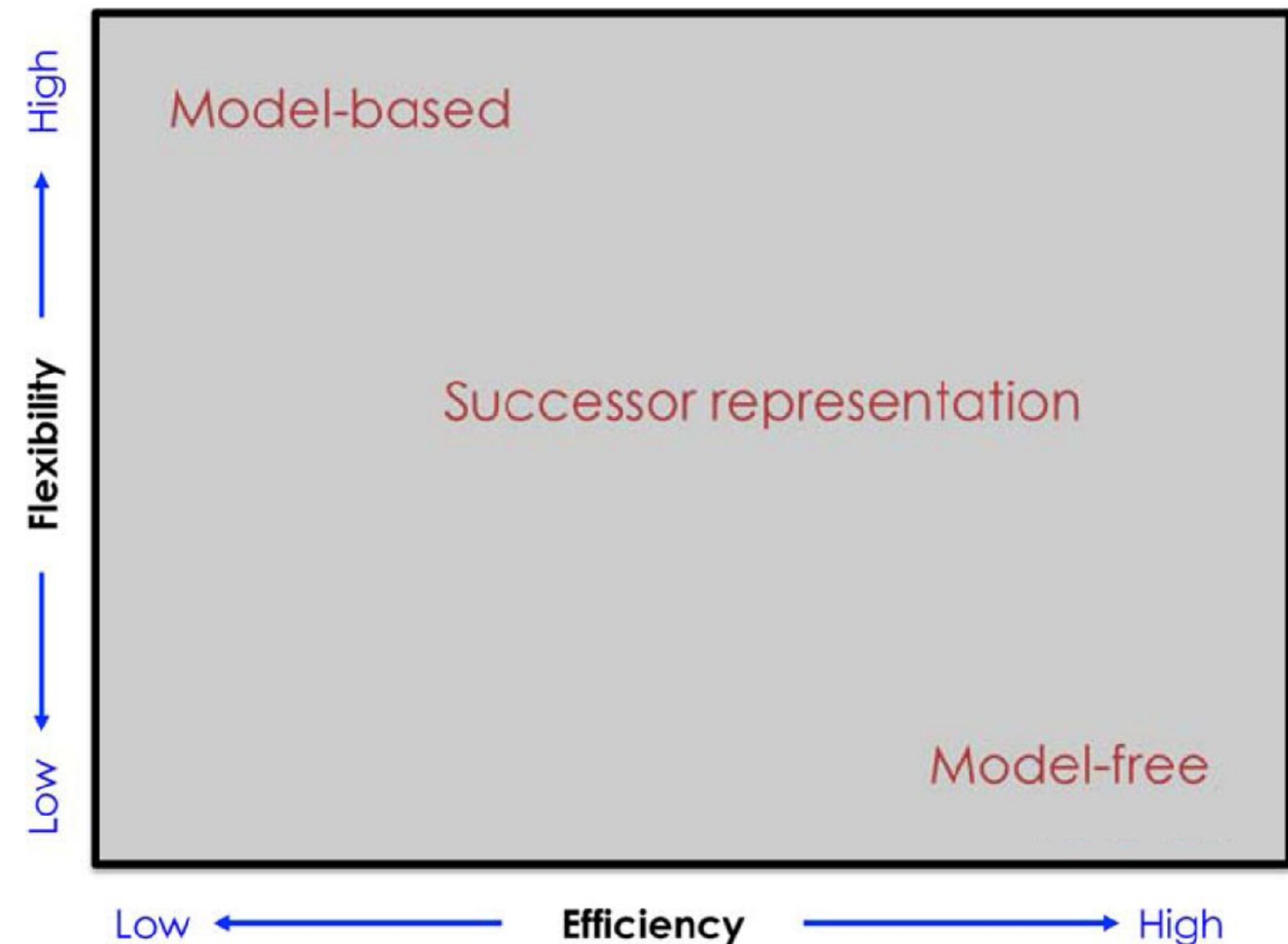
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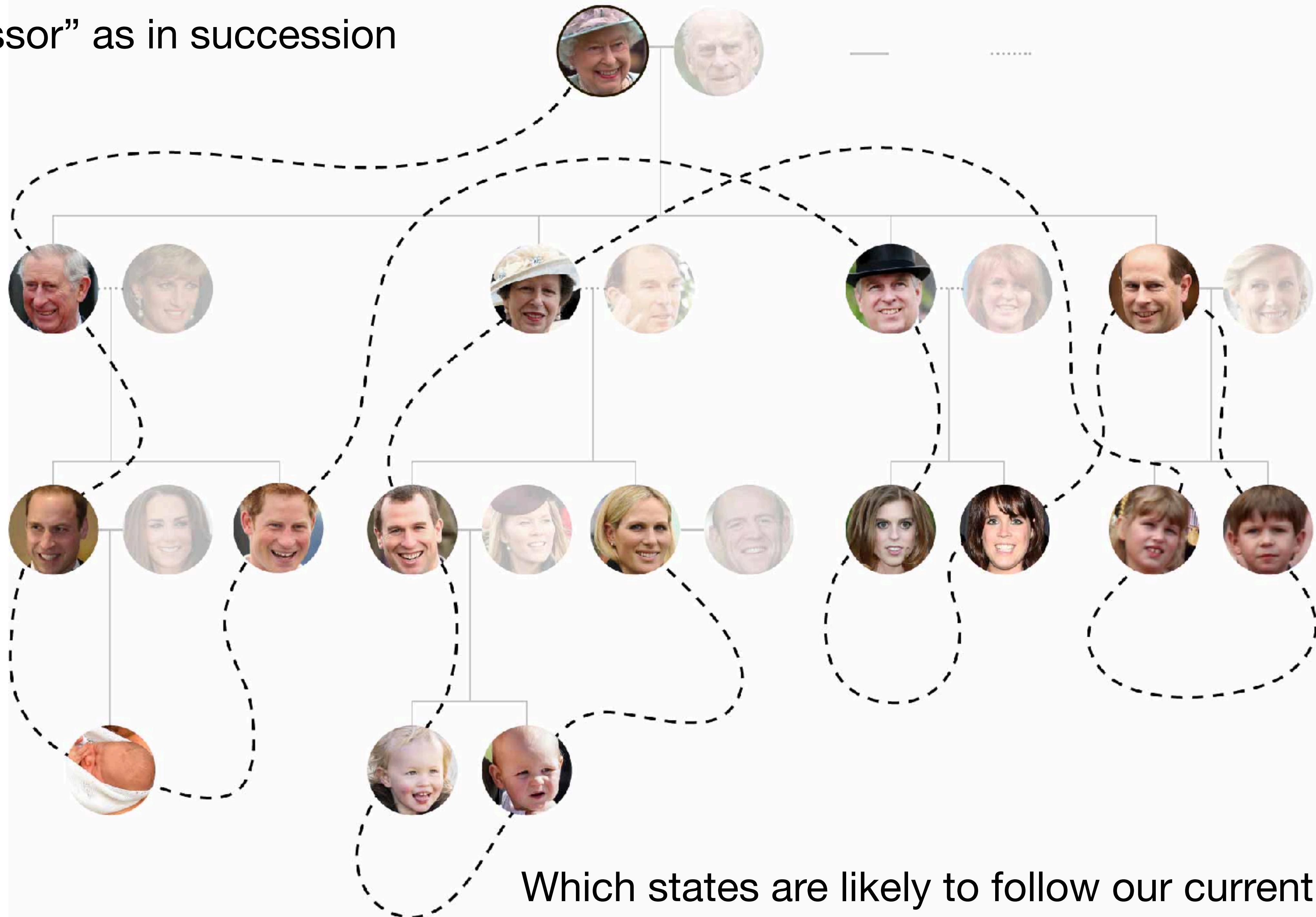
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Gershman (2018)

“Successor” as in succession



SR as a decomposition of the TD value function



Dayan (1993)

$$V^\pi(s) = \mathbb{E}_{a \sim \pi} \left[\sum_{t=0}^{\infty} \gamma^t r_t \right]$$

Value function from TD Learning

SR as a decomposition of the TD value function



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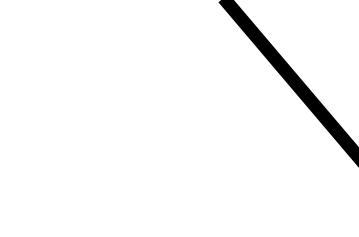
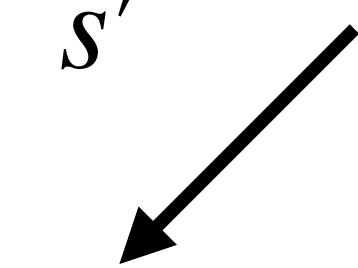
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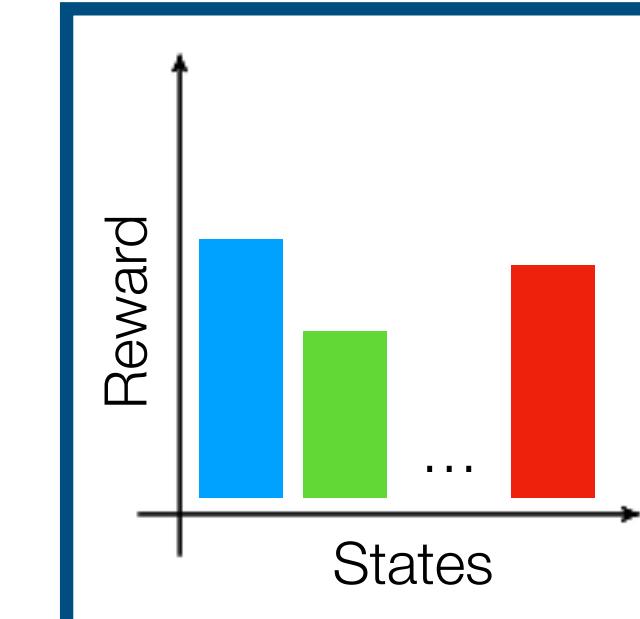
SR decomposition

s'



Successor Representation

S by S matrix of future discounted state occupancies

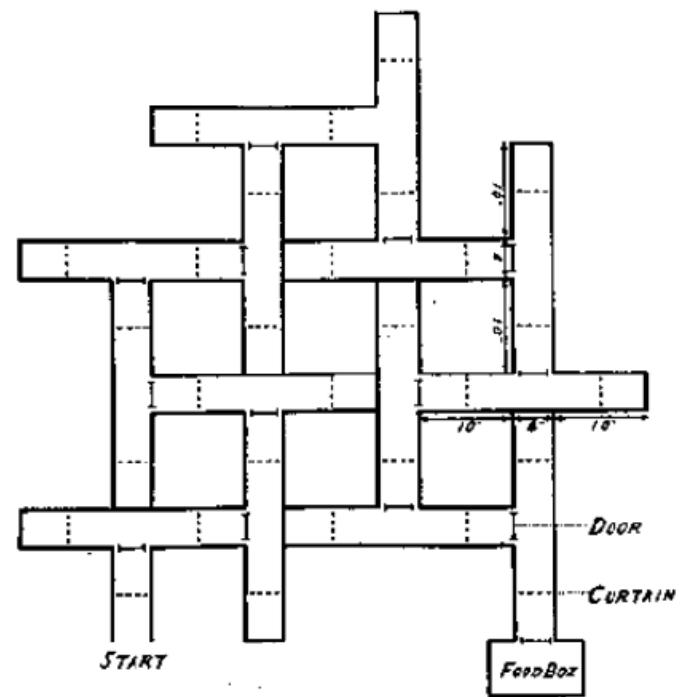


Reward Values

vector of singular rewards for each state

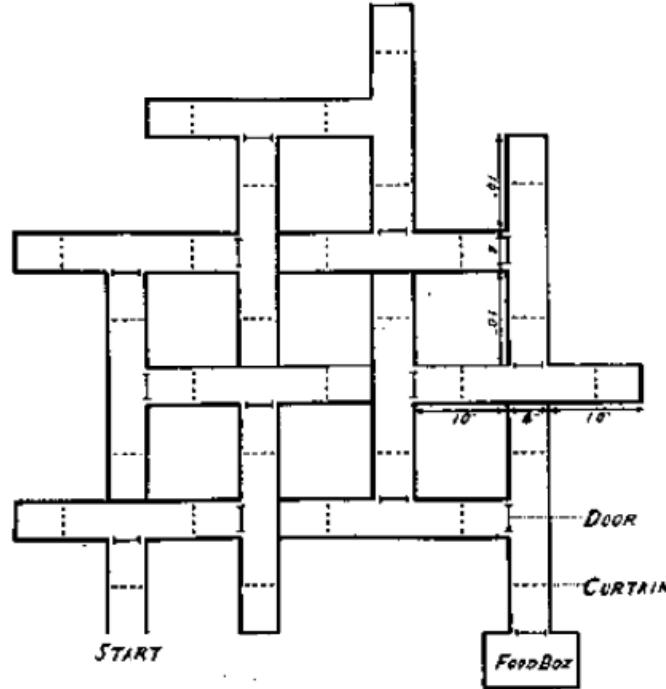
Successor Representation

Not just a map...

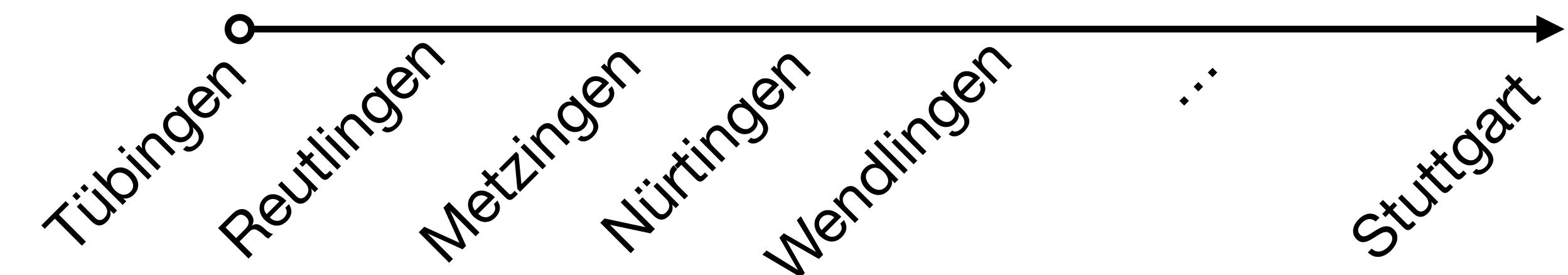


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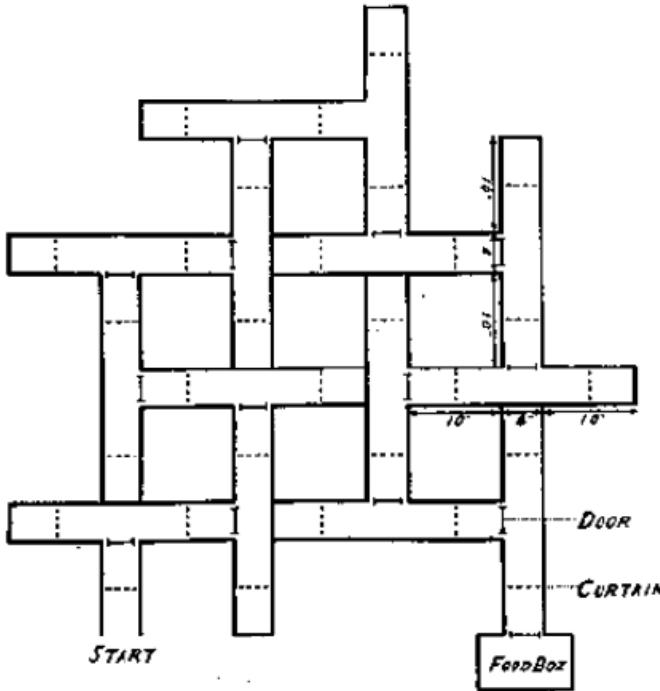


... but a goal-directed representation about which states are likely to be encountered given a policy

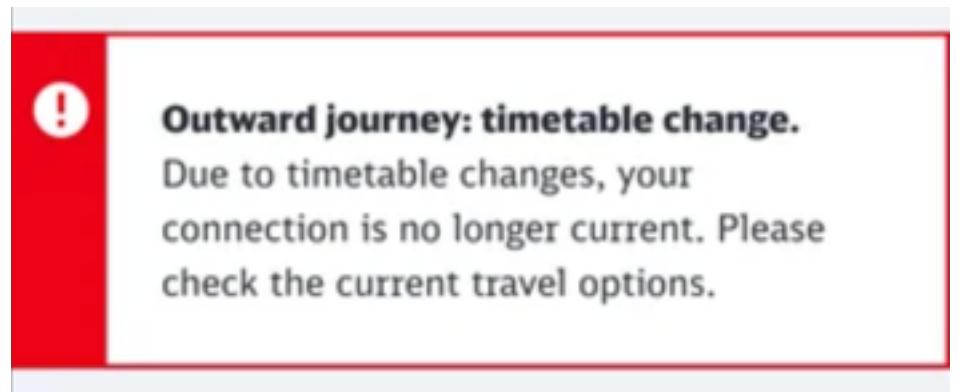
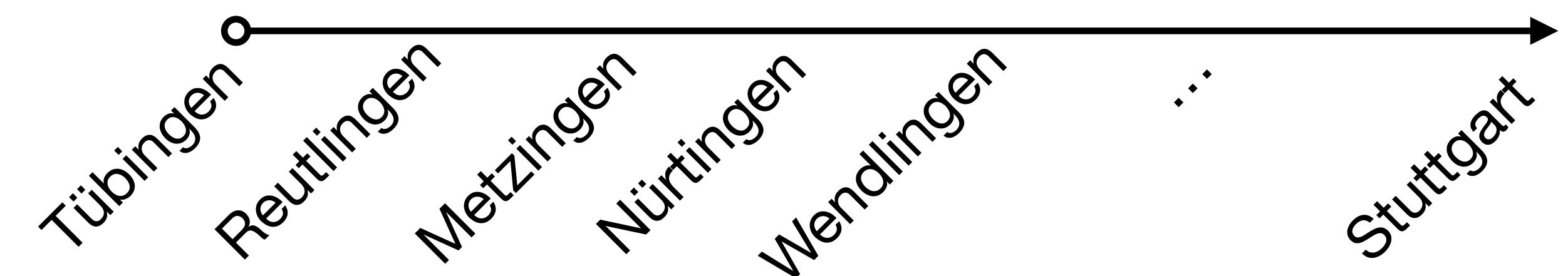


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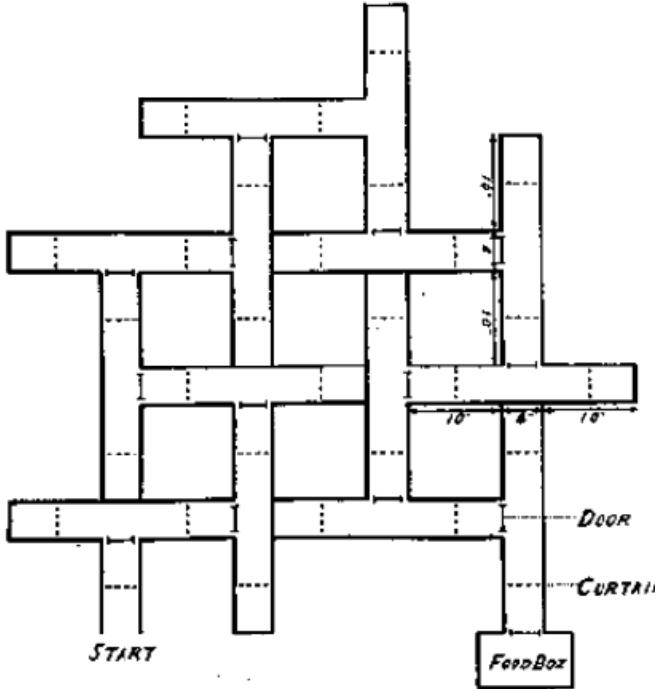


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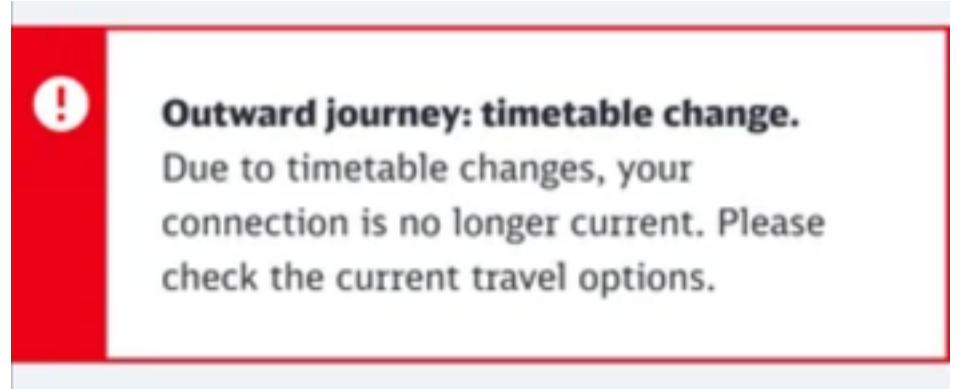
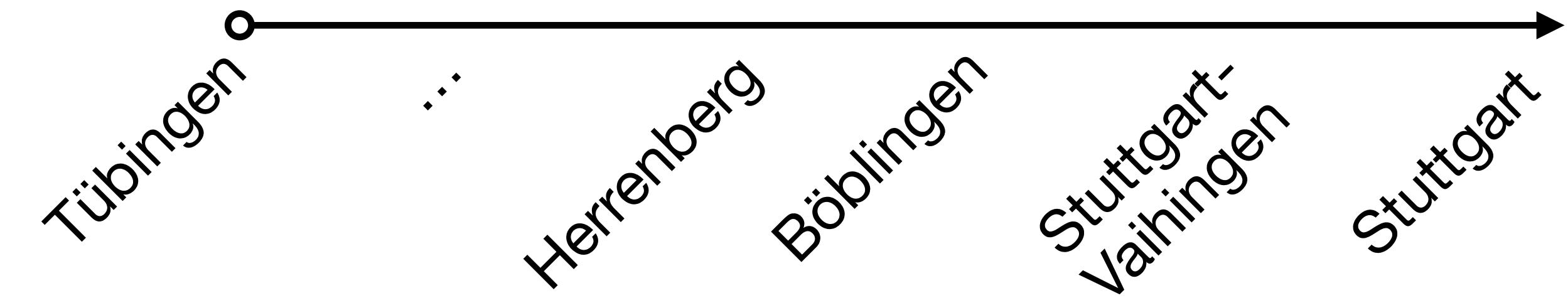


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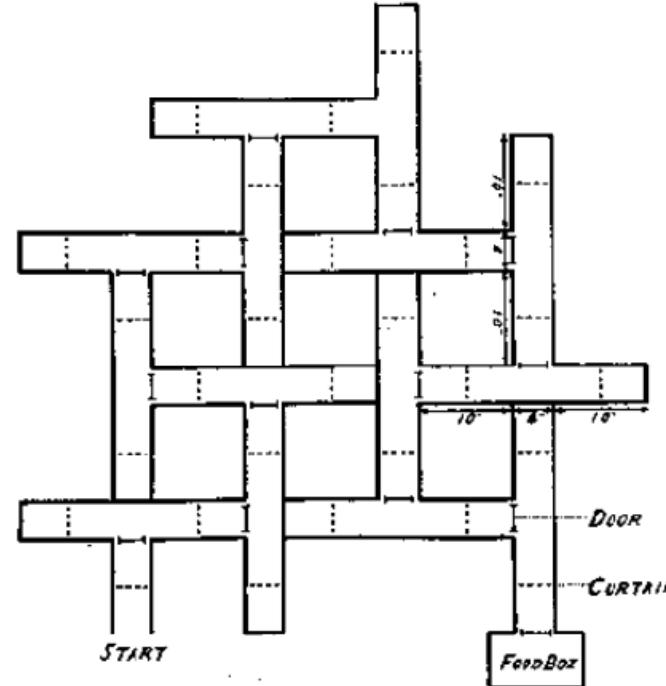


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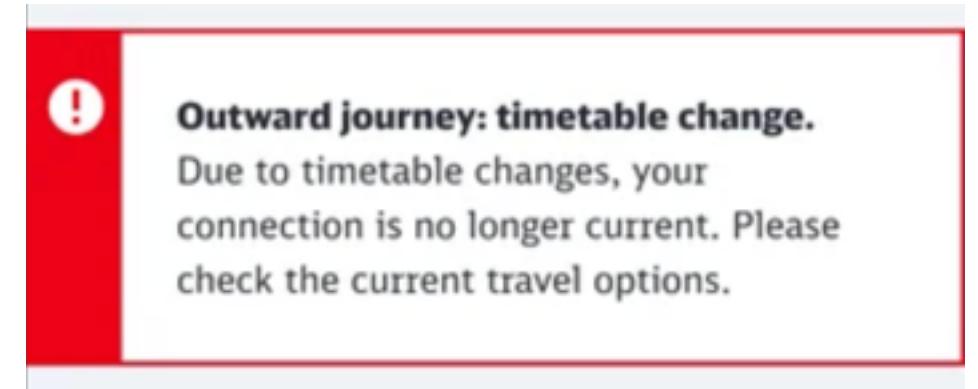
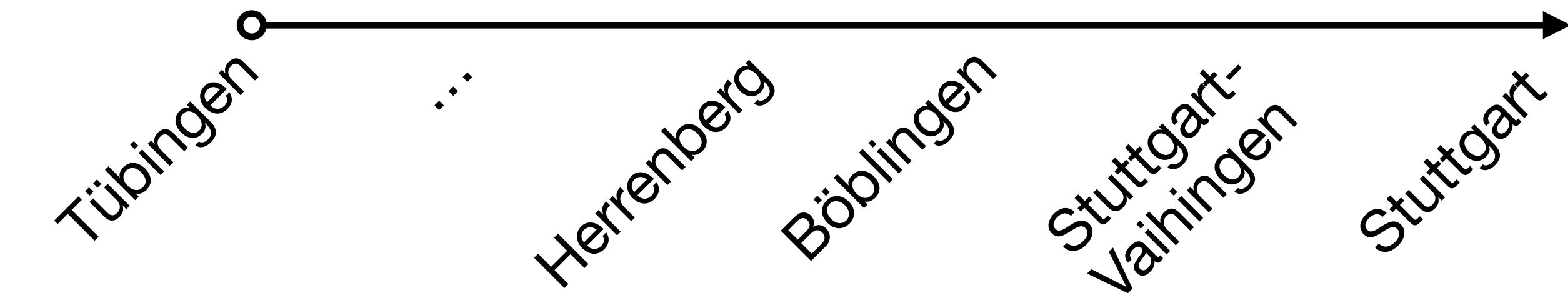


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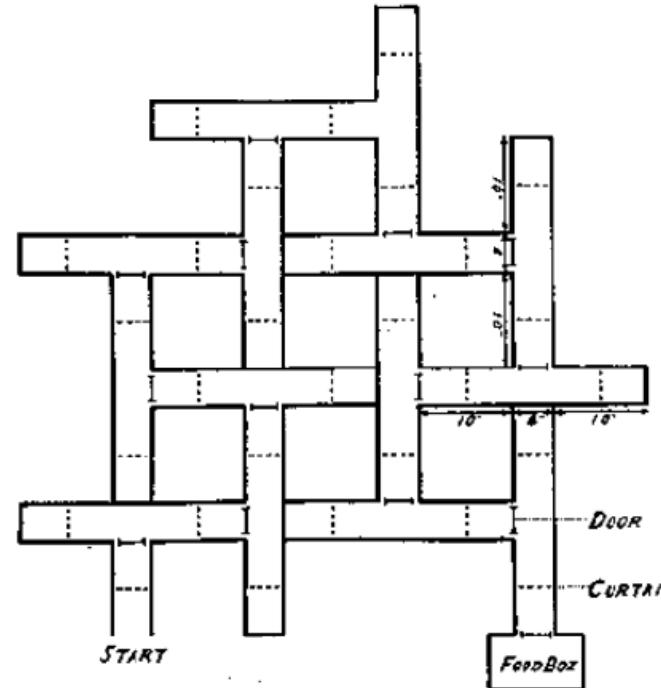
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$$M(s, s') = \mathbb{E}_\pi \left[\sum_{t=0} \gamma^t \delta(s_t = s') \mid s_0 = s \right]$$

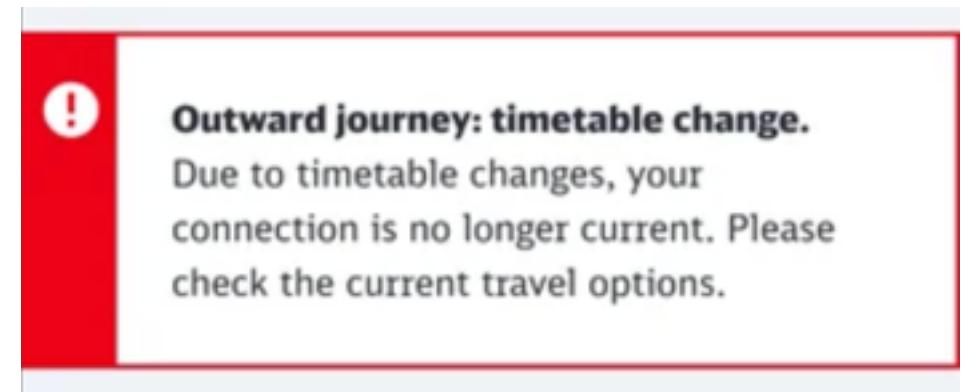
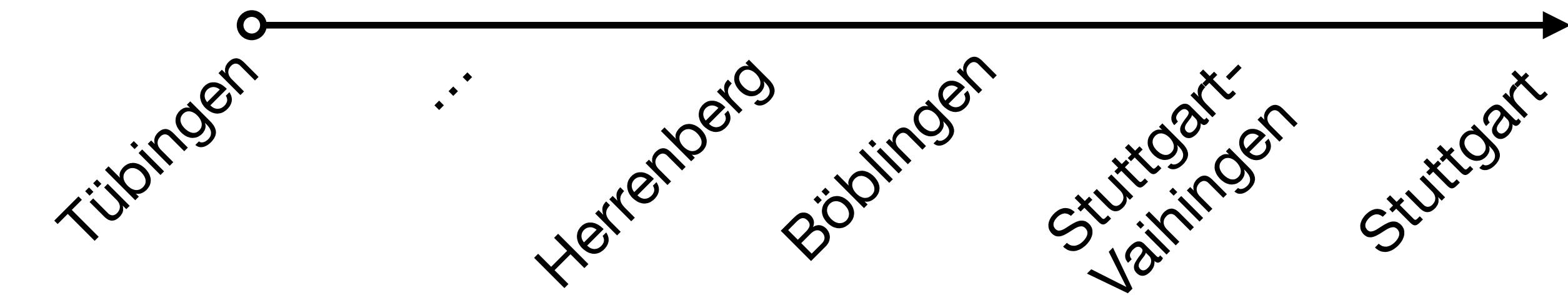
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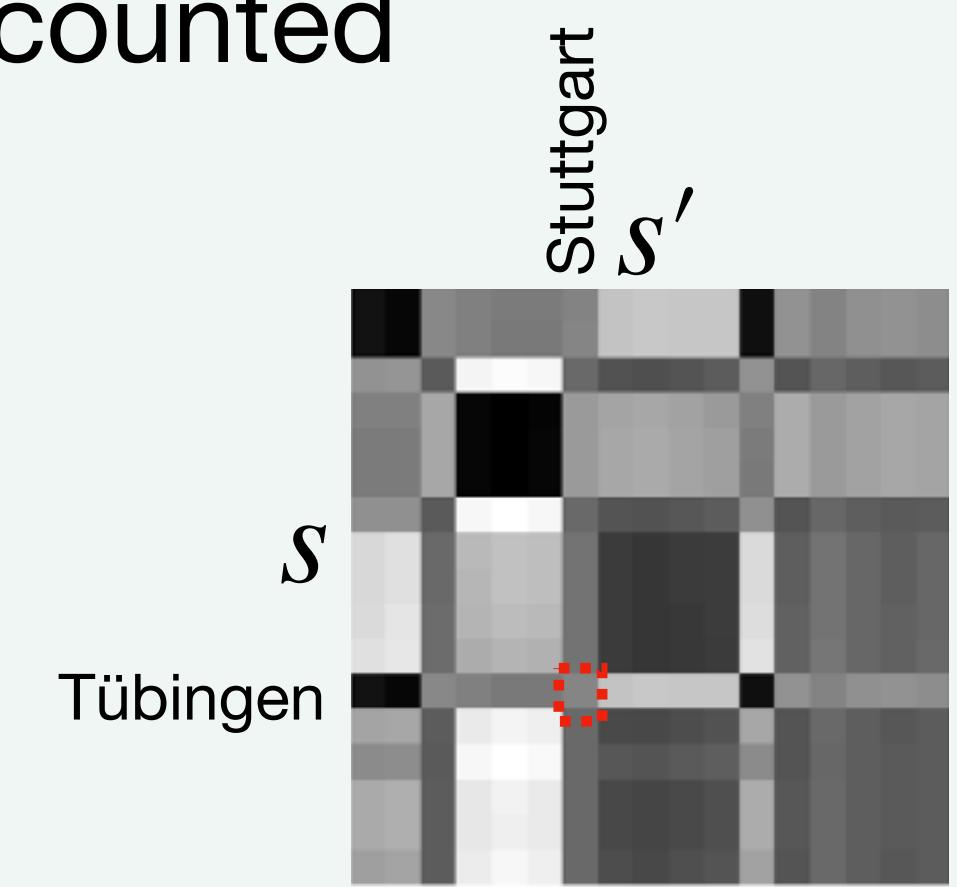


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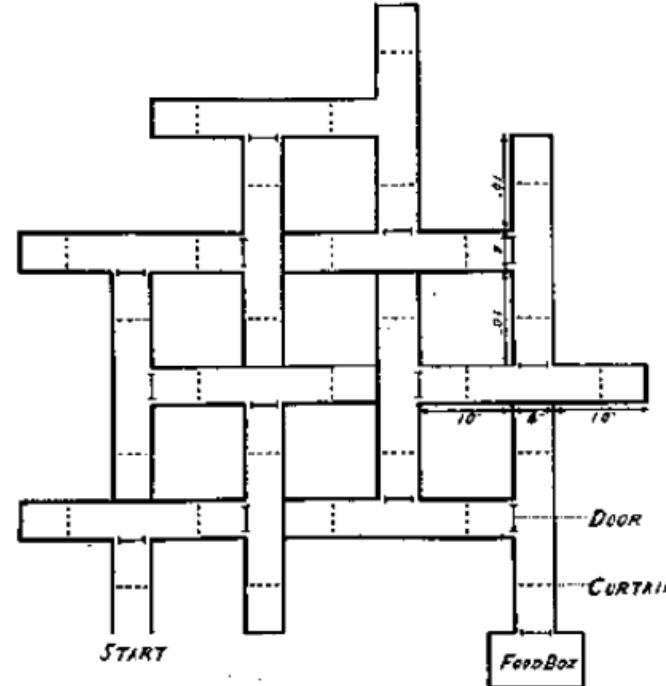
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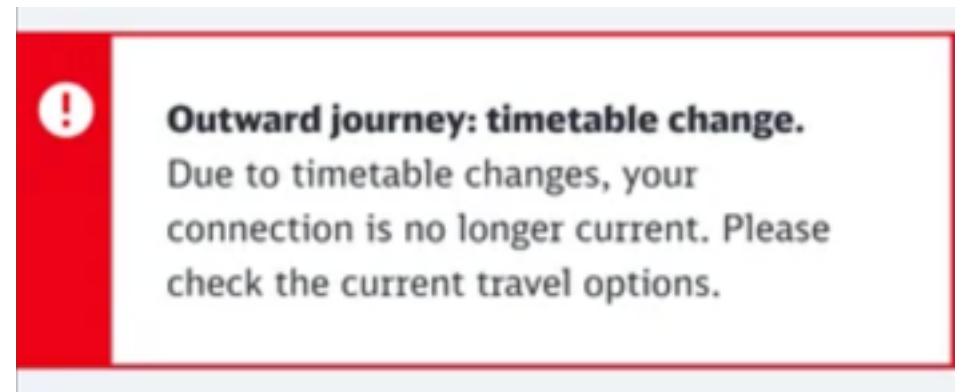
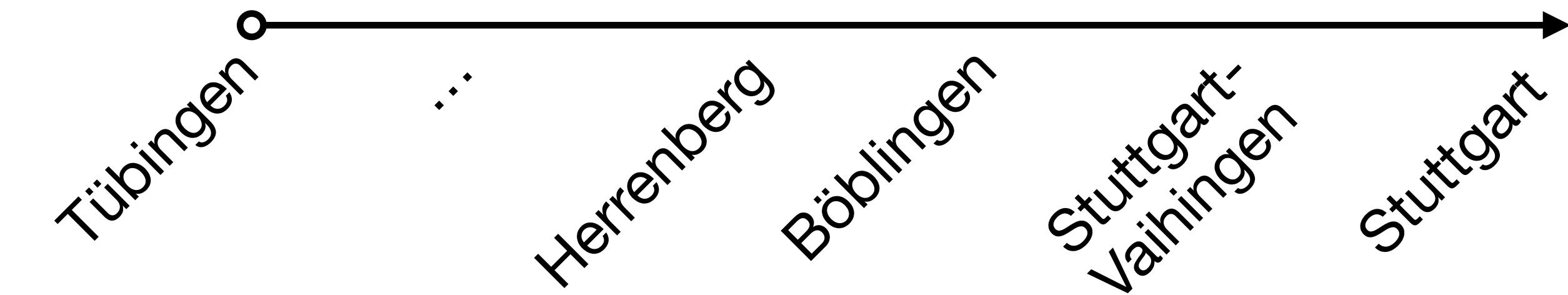
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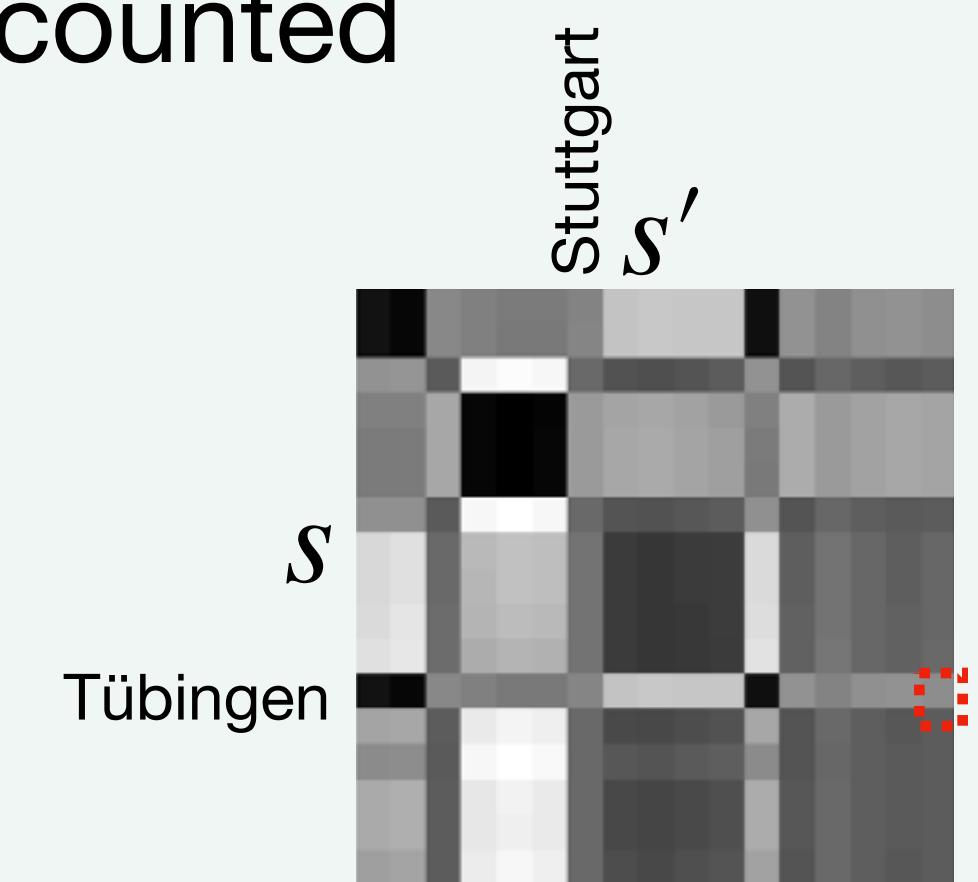


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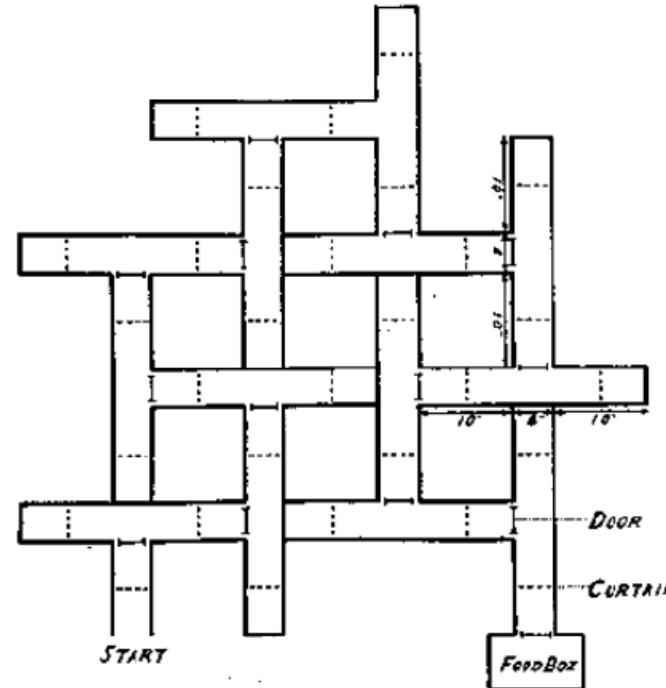
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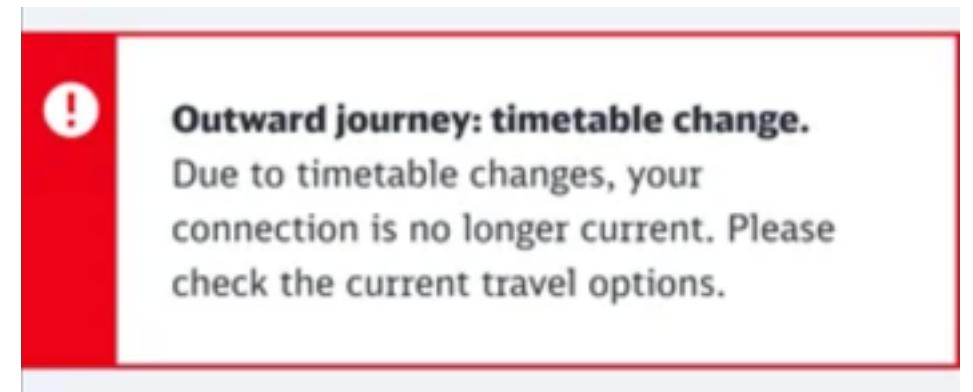
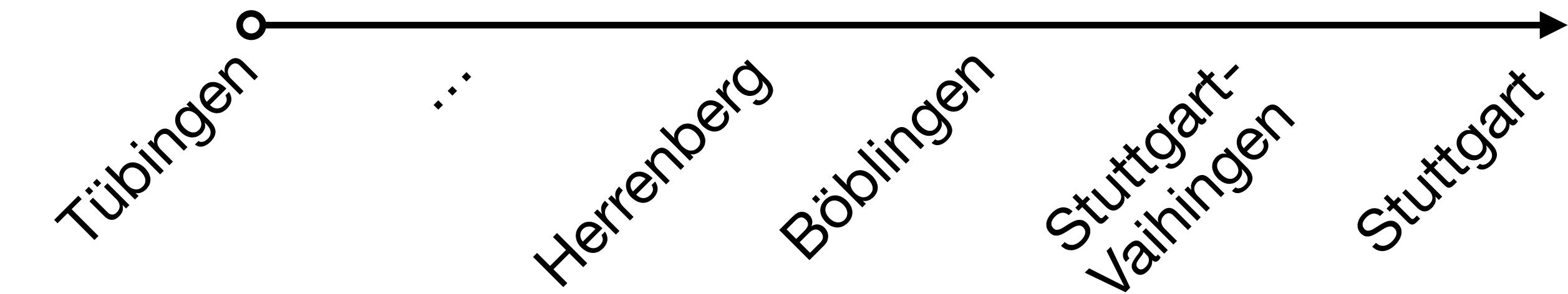
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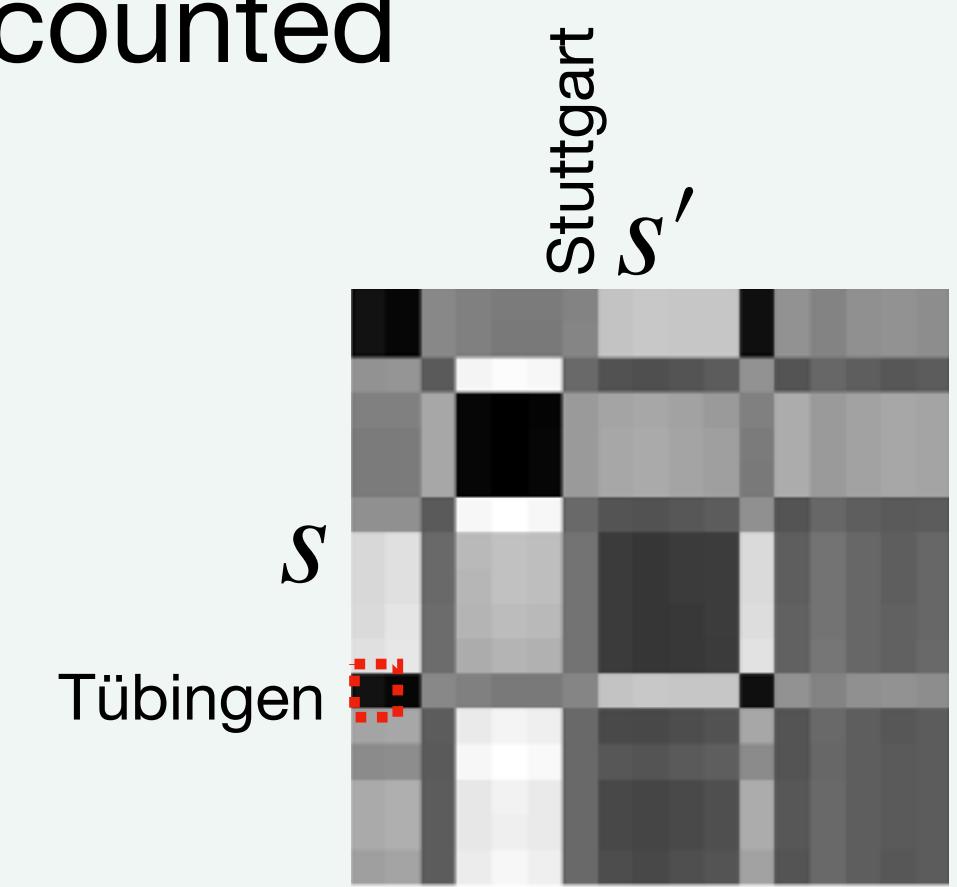


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Computing the Successor Representation (off-policy)

If the state space is fully known, we can compute the SR in closed form:

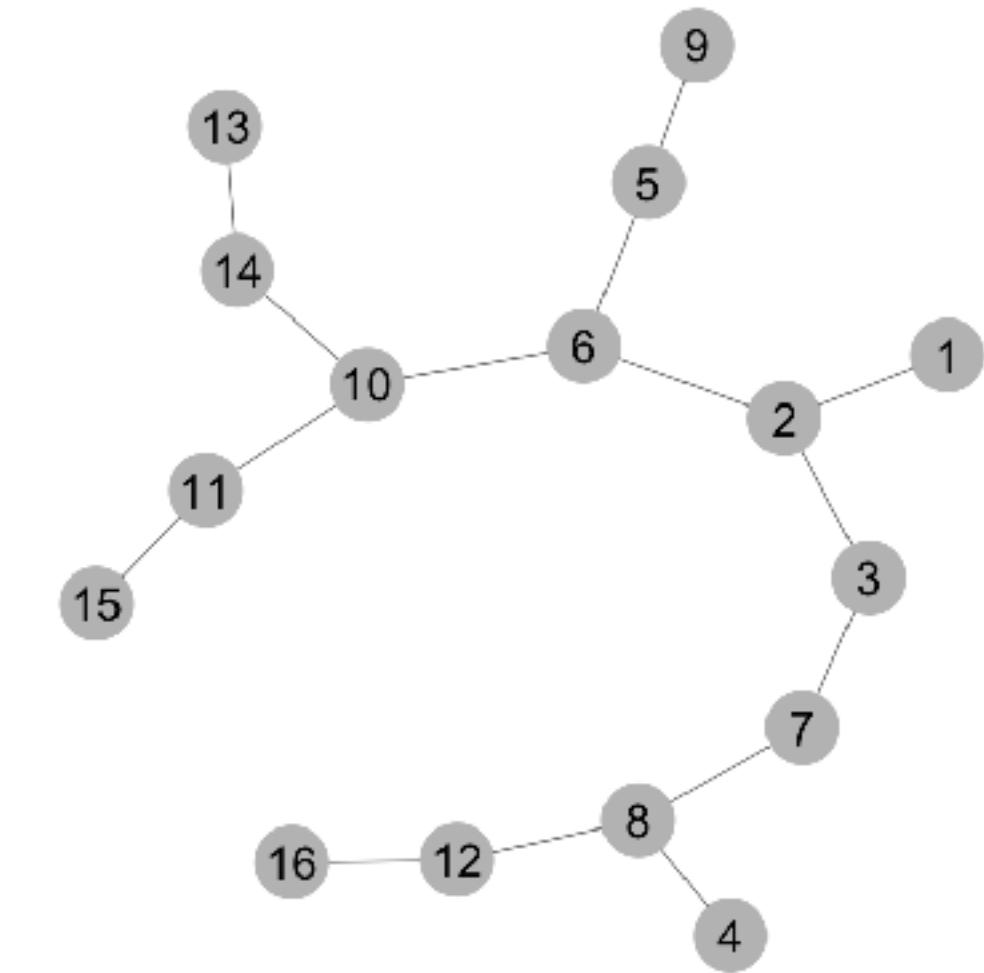
$$M(s, s') = \sum_{t=0}^{\infty} \gamma^t T^t = (I - \gamma T)^{-1}$$

I is the identity matrix, γ is the temporal discount factor

$$T \text{ is the transition matrix under a policy: } T(s, s') = \sum_a \pi(a | s) P(s' | s, a)$$

A further simplification that is often used is to assume a random policy, allowing us to define T using the degree (D) and adjacency (A) matrices

$$T = D^{-1}A$$



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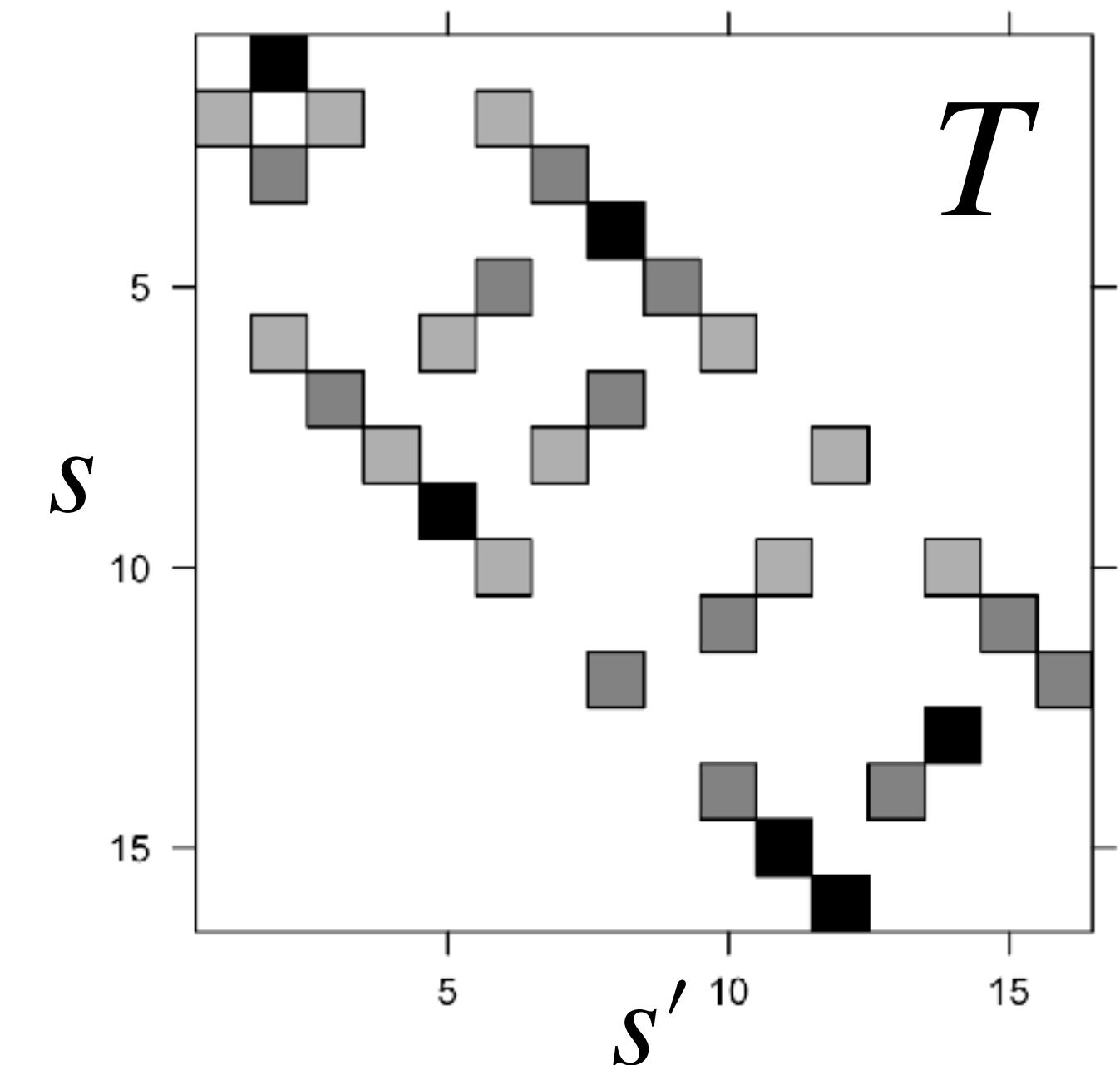
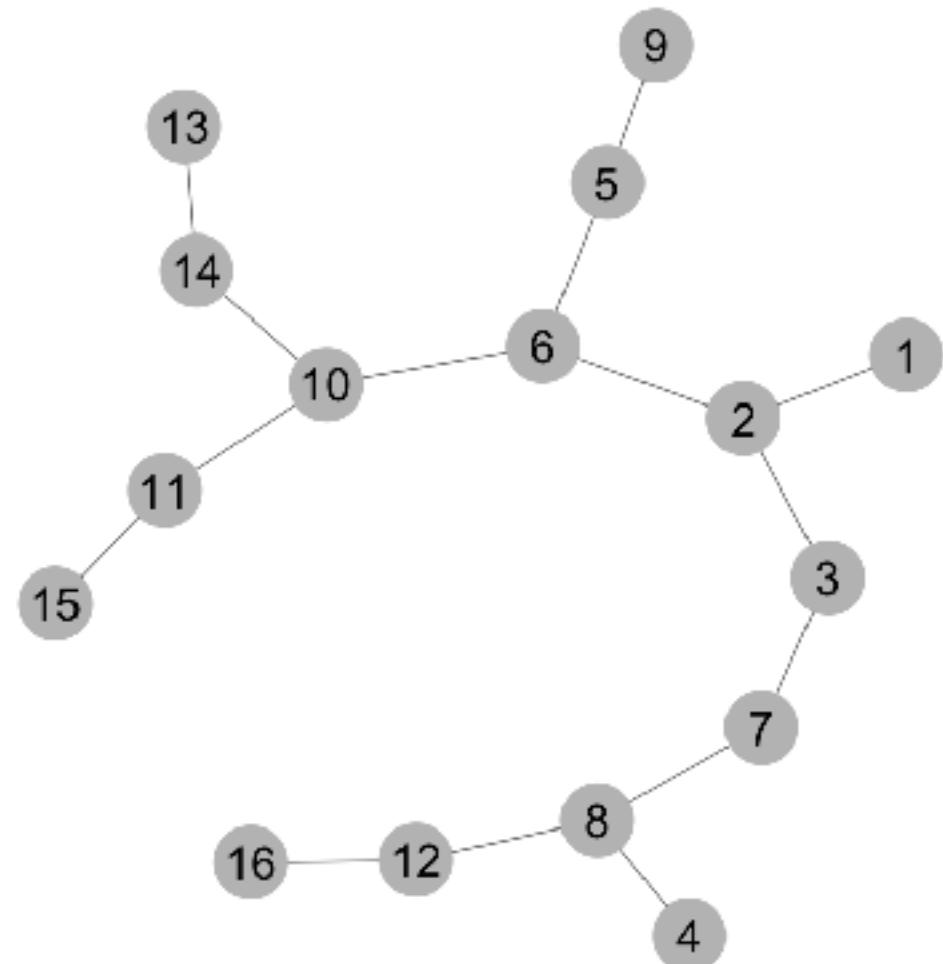
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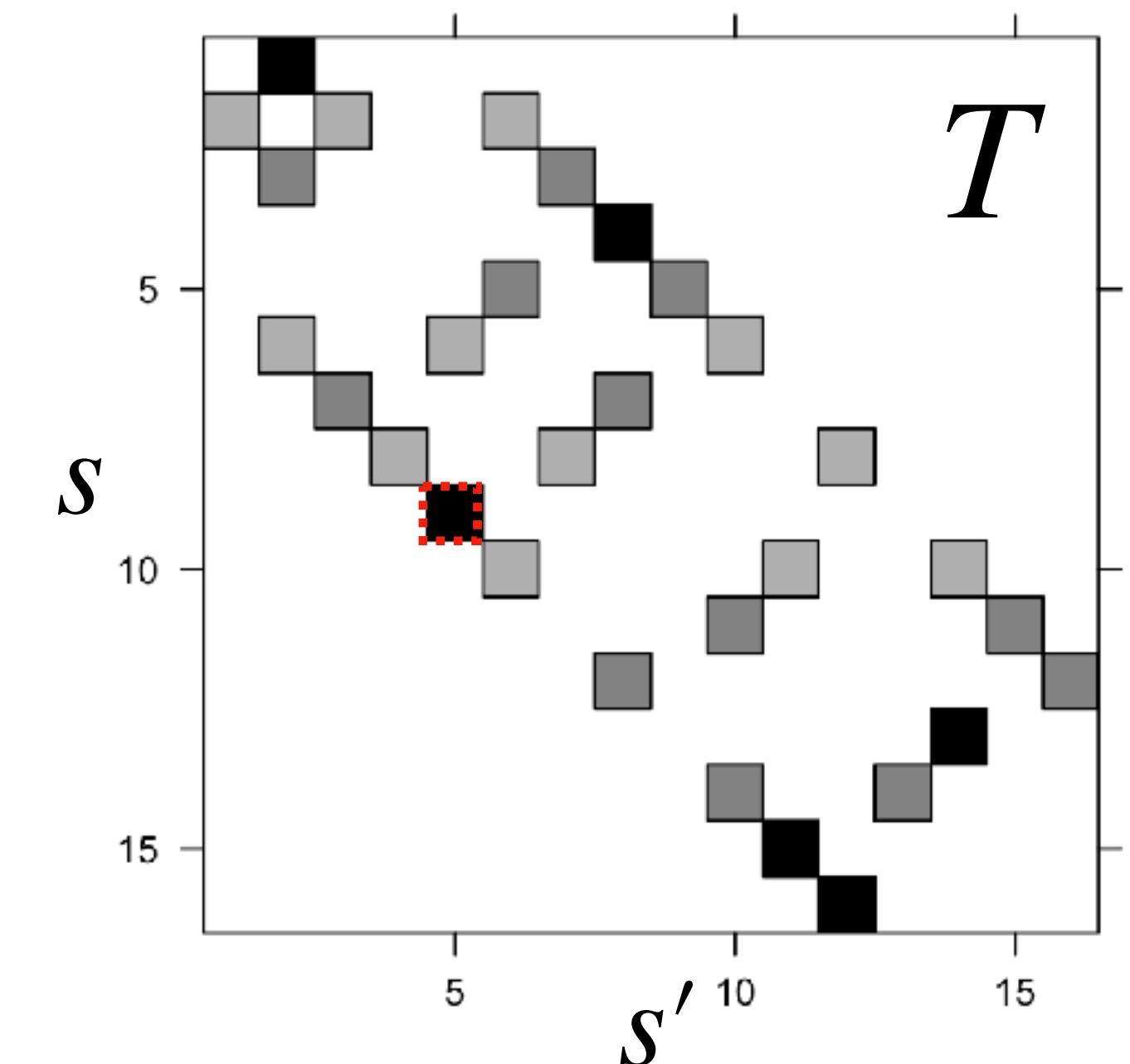
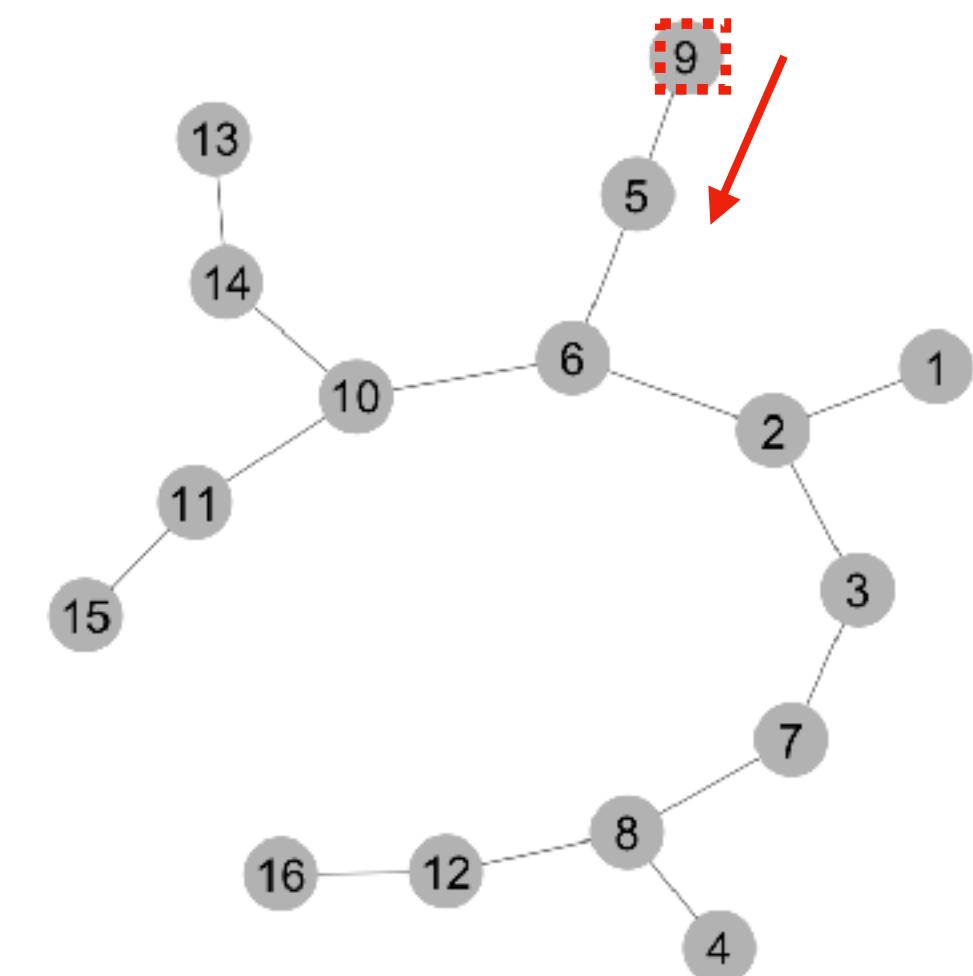
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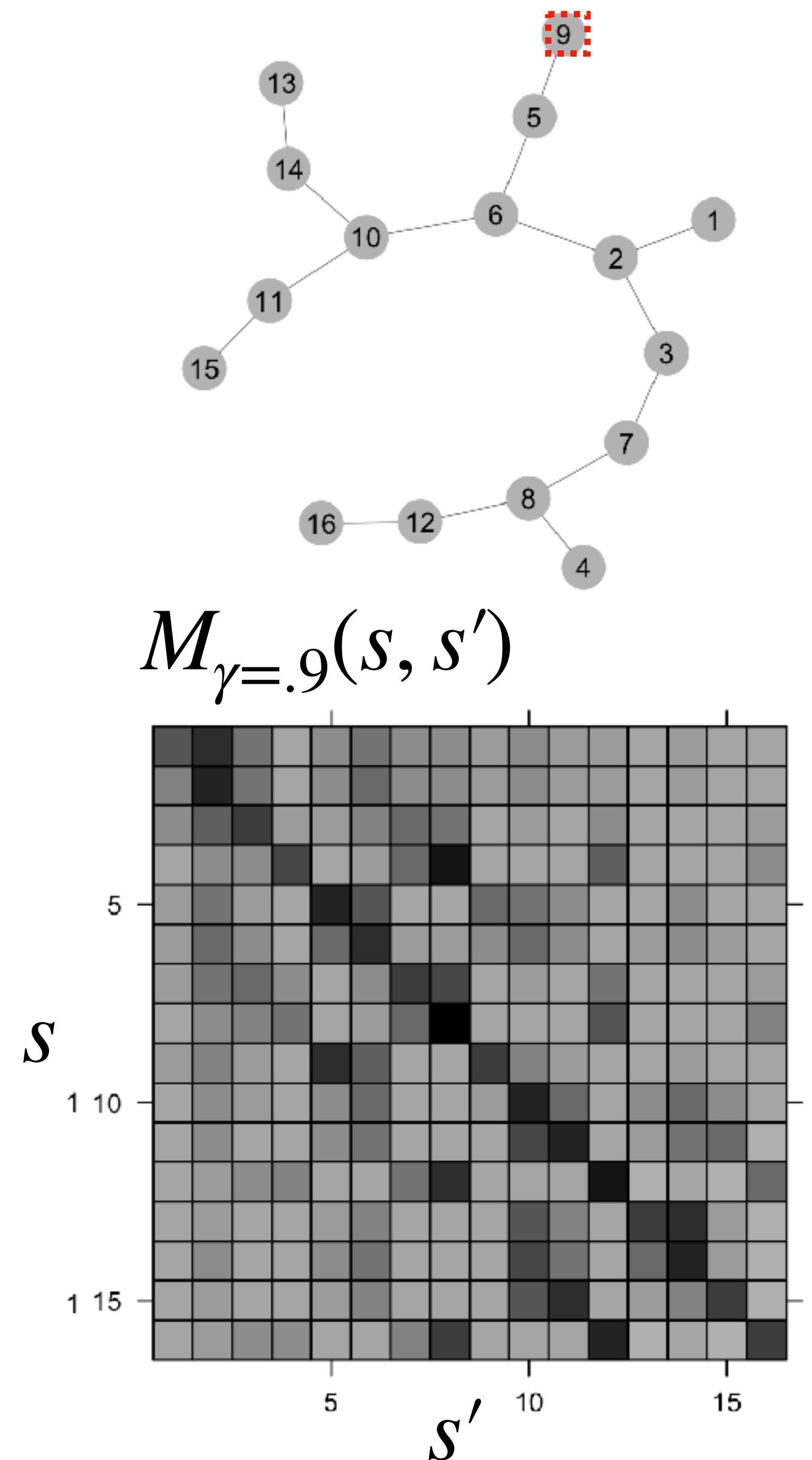
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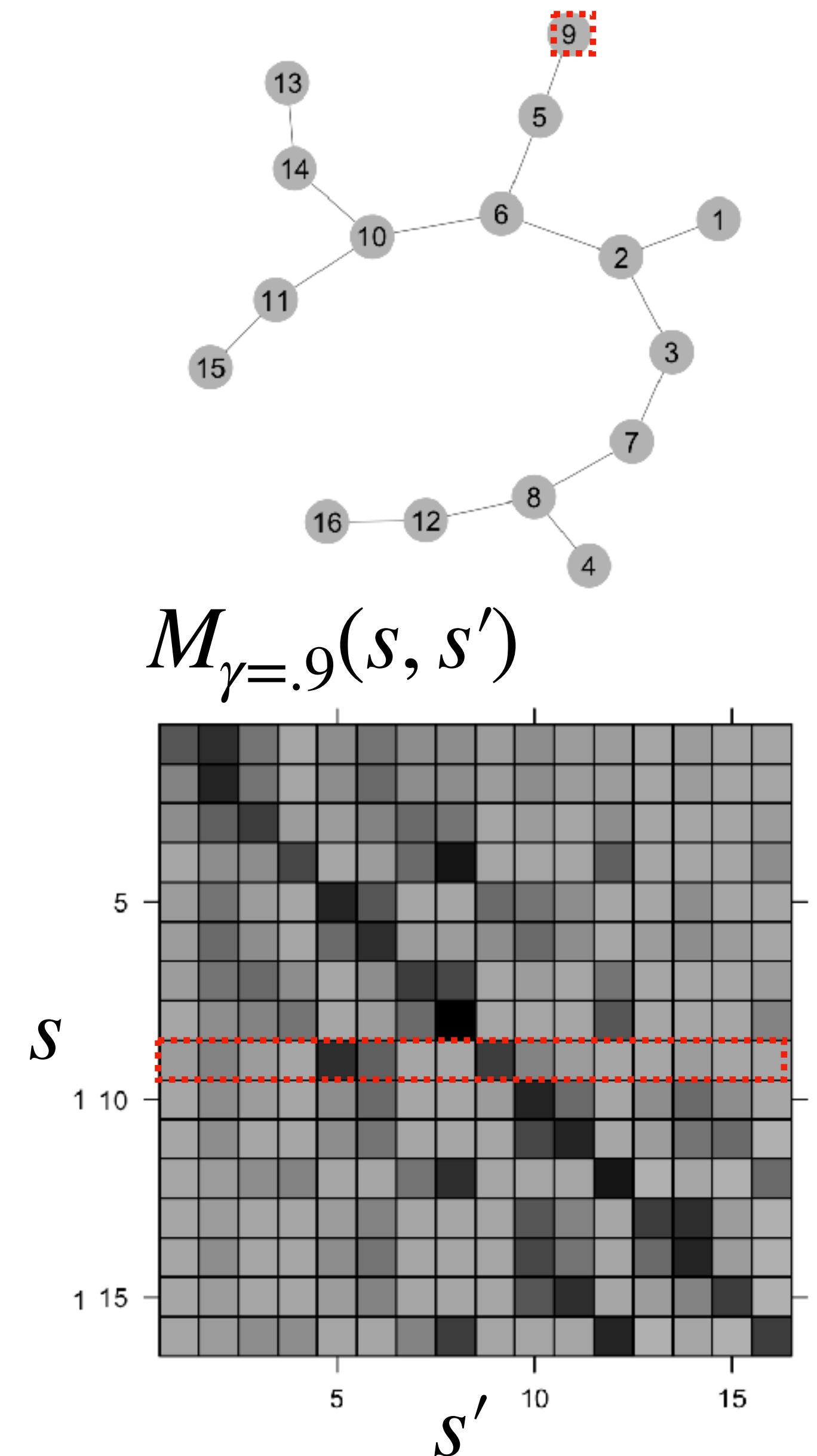
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Computing the Successor Representation (on policy)

If the state space is not known, we can compute the SR using the delta-rule:

$$\hat{M}_{t+1}(s_t, s') = \hat{M}_t(s_t, s') + \alpha \left[\delta(s_t = s') + \gamma \hat{M}_{t+1}(s_t, s') - \hat{M}_t(s_t, s') \right]$$

where α is the learning rate and δ is the kronecker delta $\delta = 1$ when true, 0 otherwise

- This update is identical to the temporal difference learning rule for value functions
- The successor representation is updated based on the *successor prediction error* instead of the *reward prediction error*

Computing the Successor Representation (on policy)

Russek et al., (2017)

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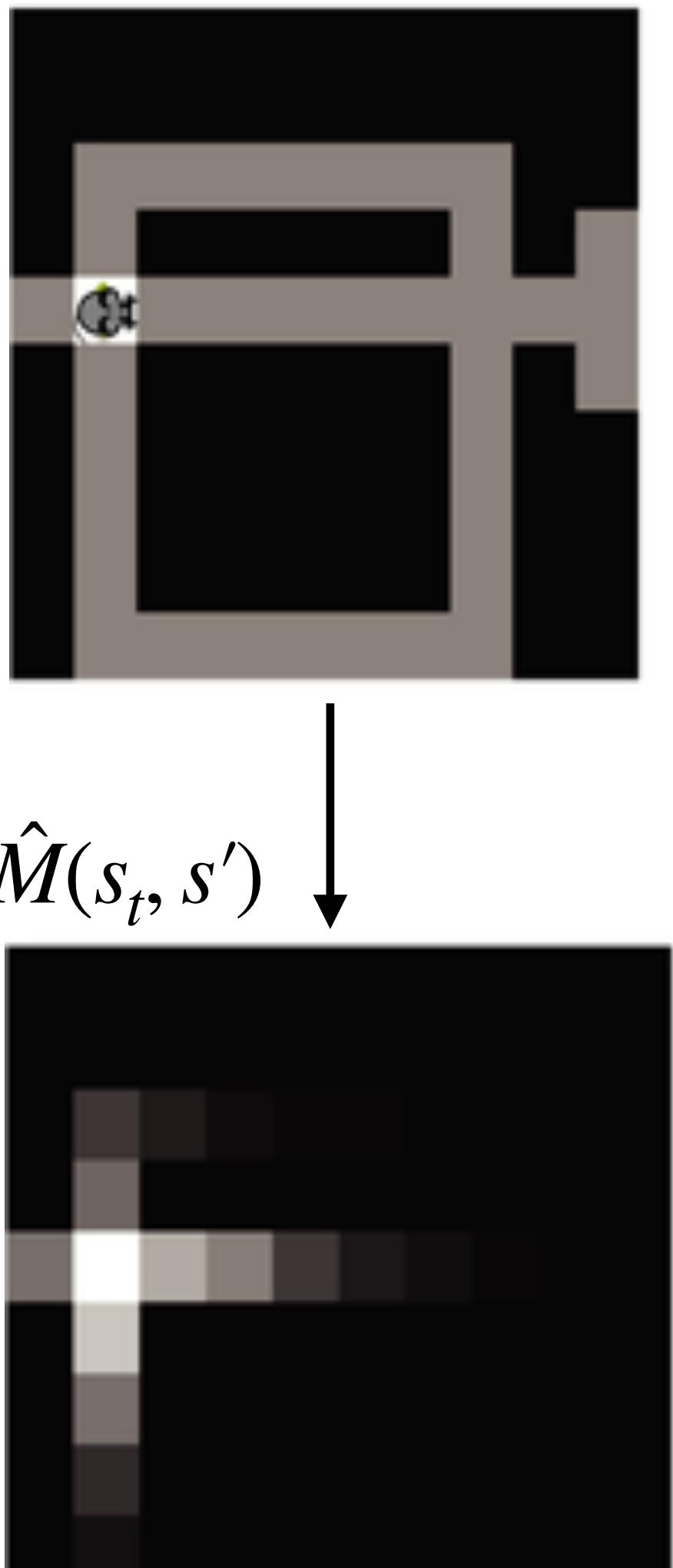
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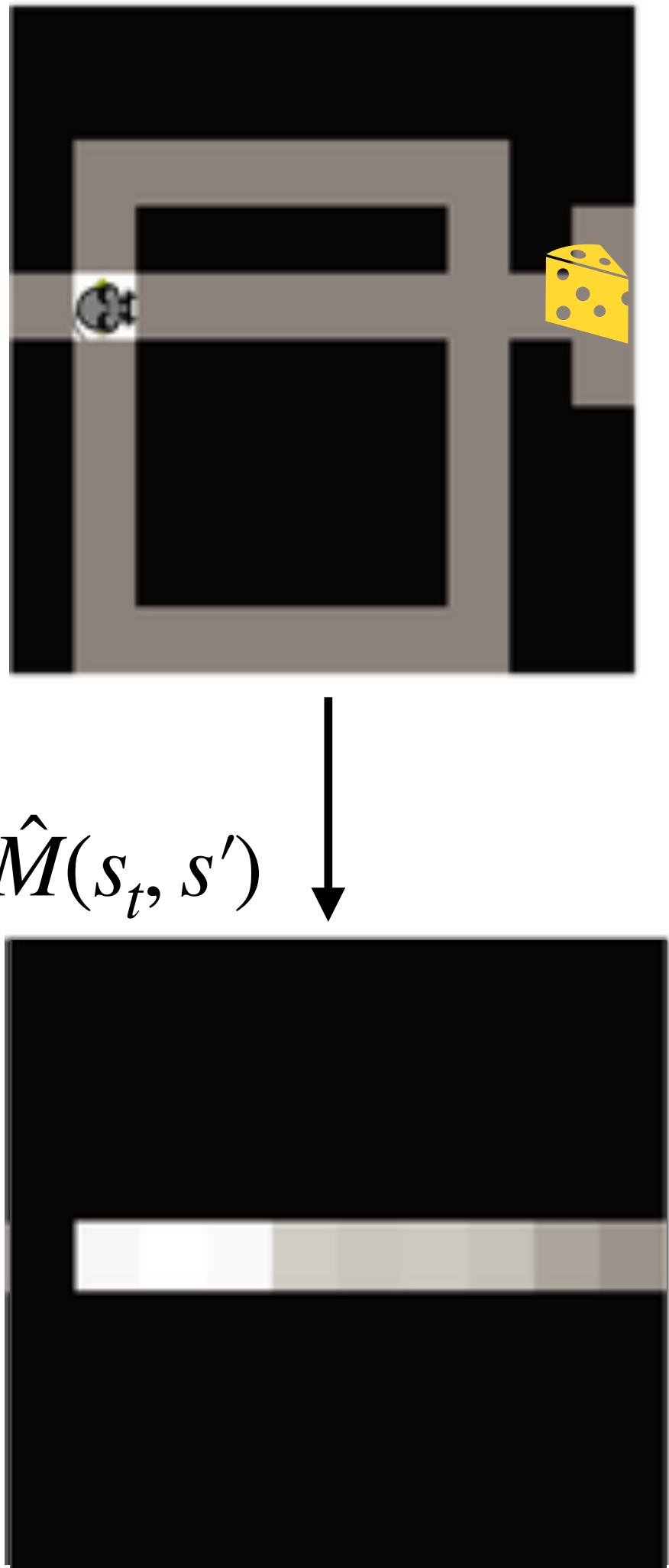
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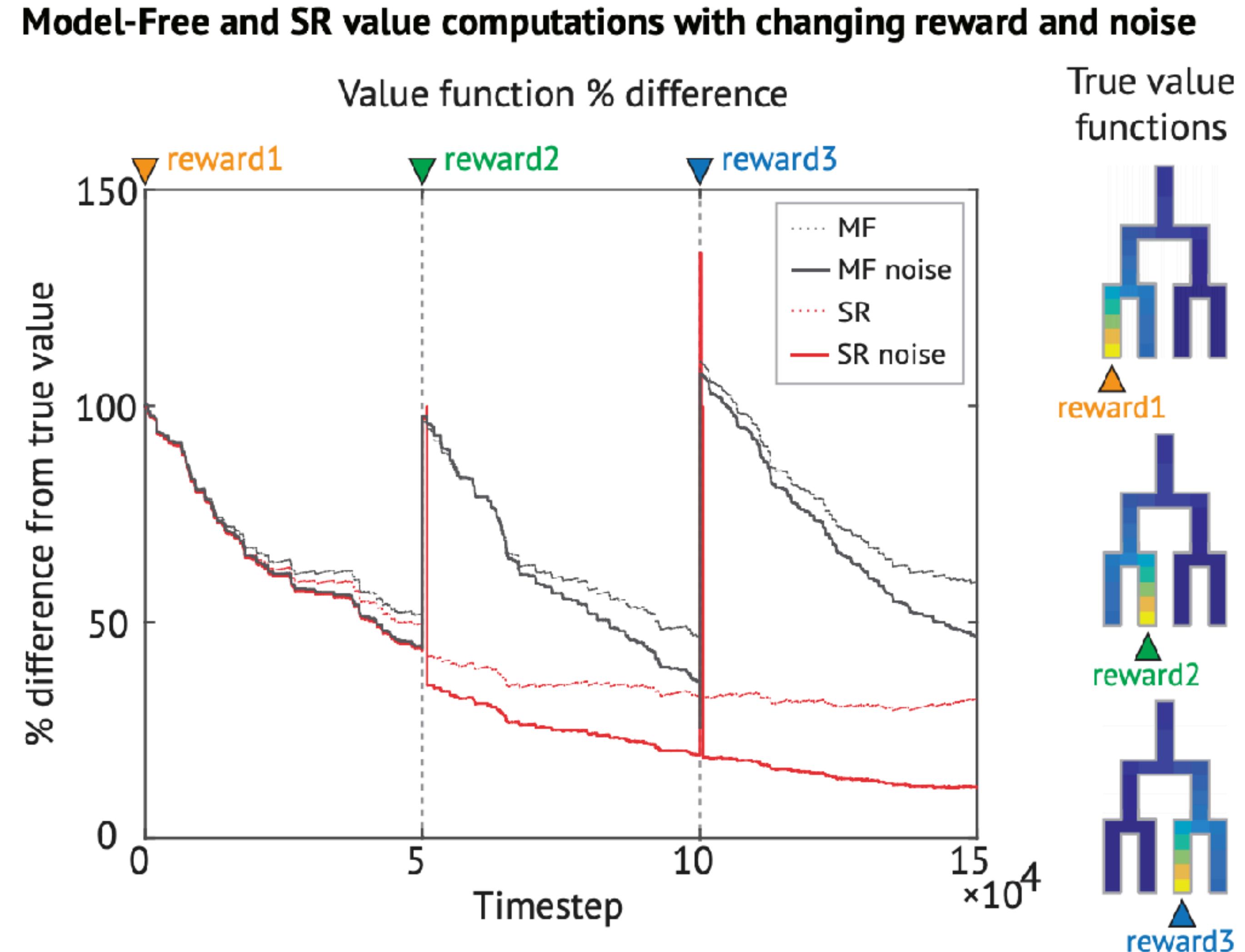


SR generalizes for changes in reward

- If the location of rewards change, only the $r(s')$ part needs to be re-learned while $M(s, s')$ remains the same

$$V^\pi(s) = \sum_{s'} M(s, s')r(s')$$

- This leads to faster generalization to changes in the environment



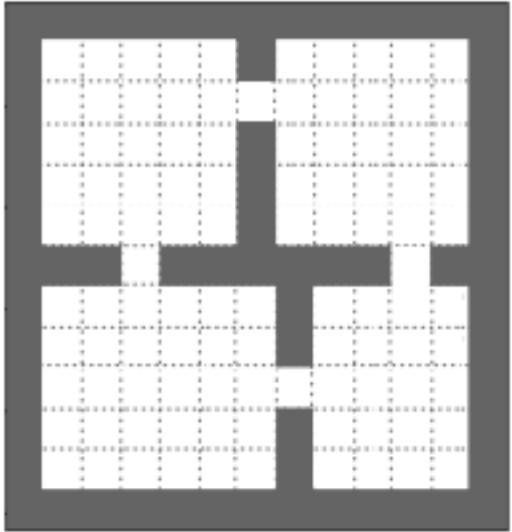
Stachenfeld, Botvinick & Gershman (2017)

The Eigenvalues of the SR

- Eigenvectors capture different dimensions of variability
 - $M = V\Lambda V^{-1}$ where $v_i \in V$ are Eigenvectors and $\lambda_i \in \Lambda$ are the Eigenvalues

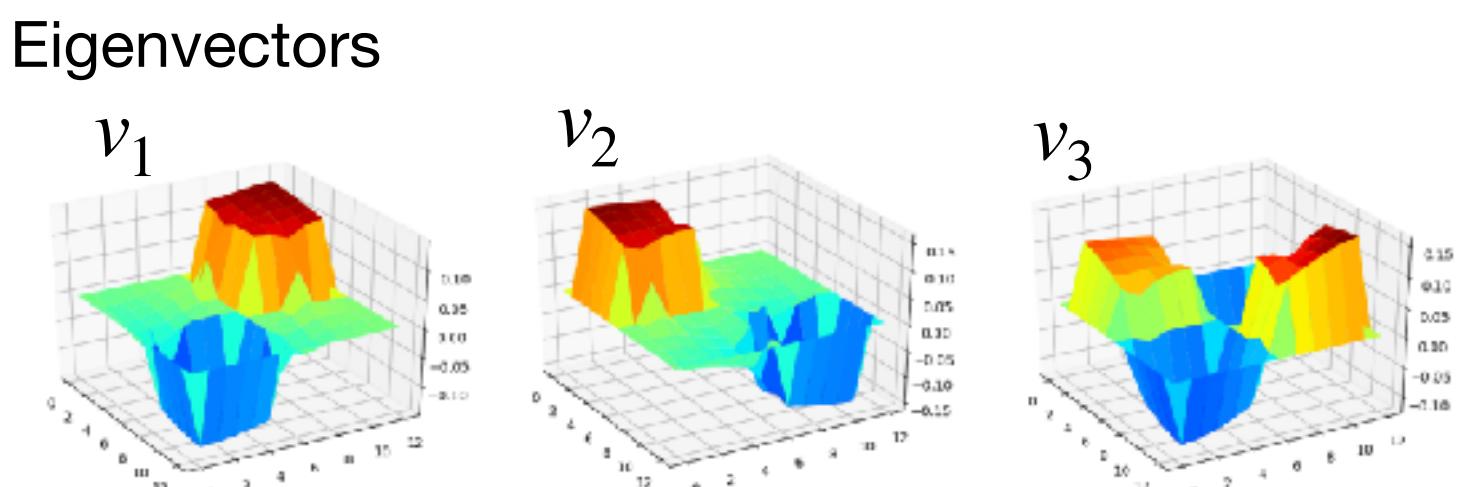
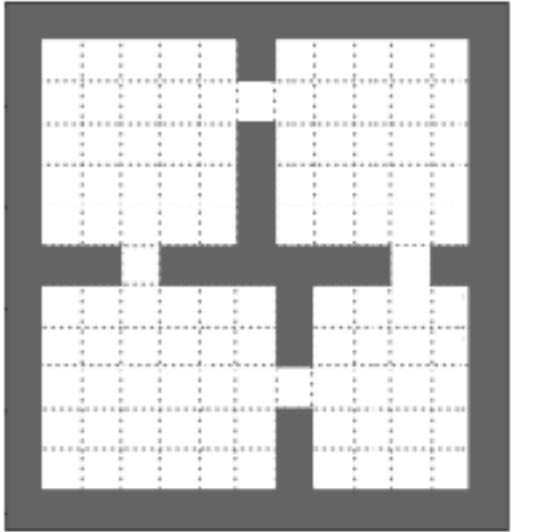
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 - $M = V\Lambda V^{-1}$ where $v_i \in V$ are Eigenvectors and $\lambda_i \in \Lambda$ are the Eigenvalues



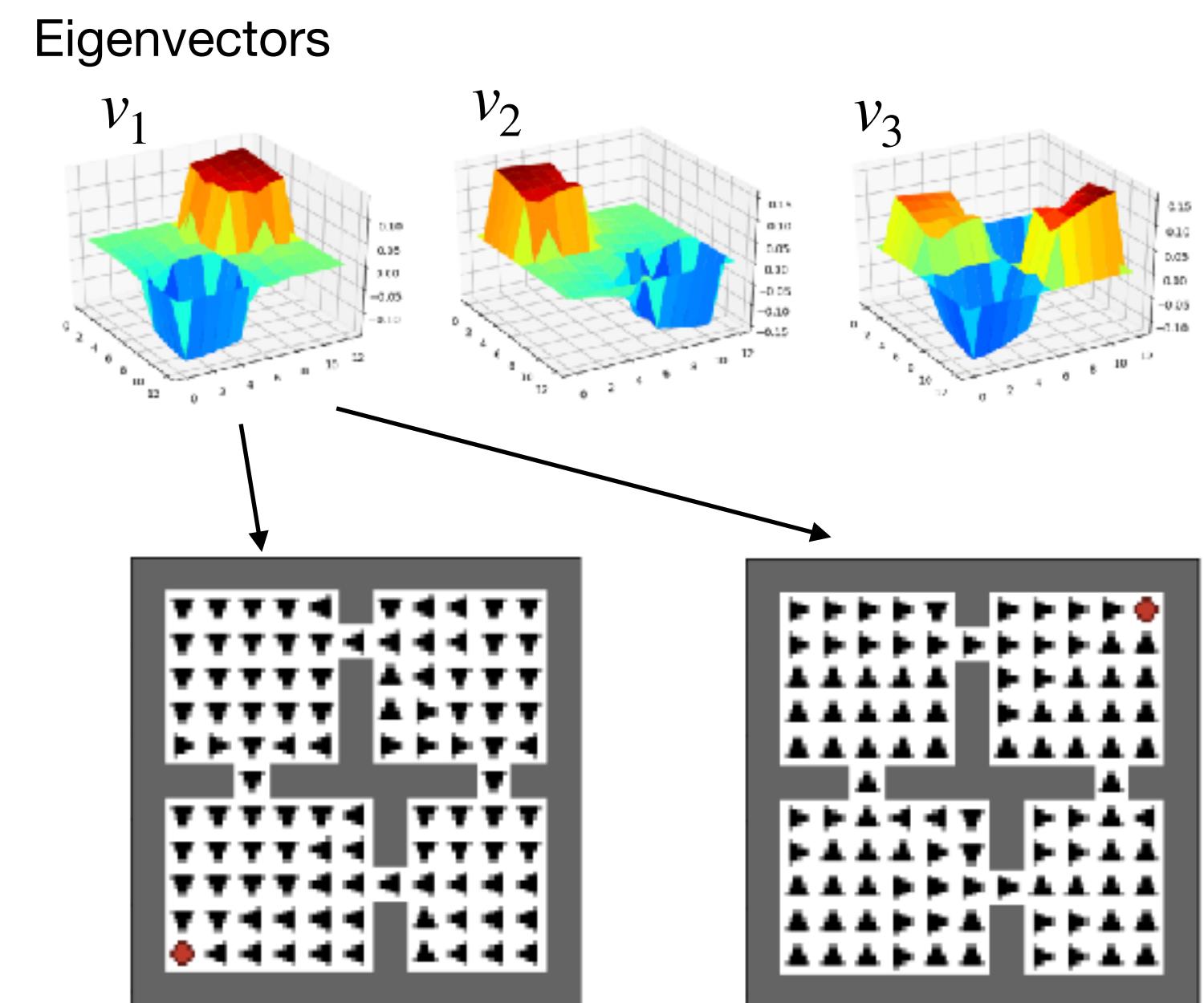
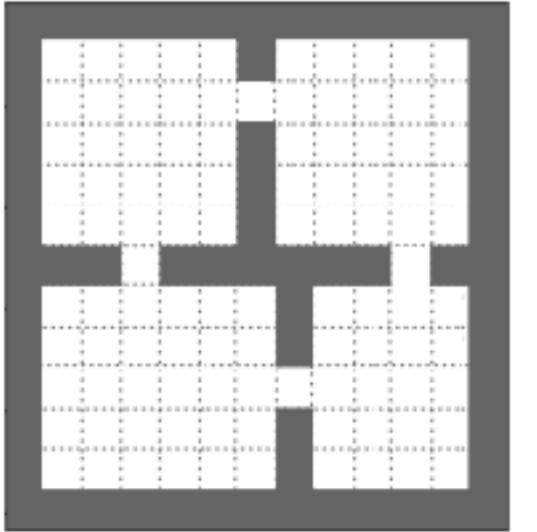
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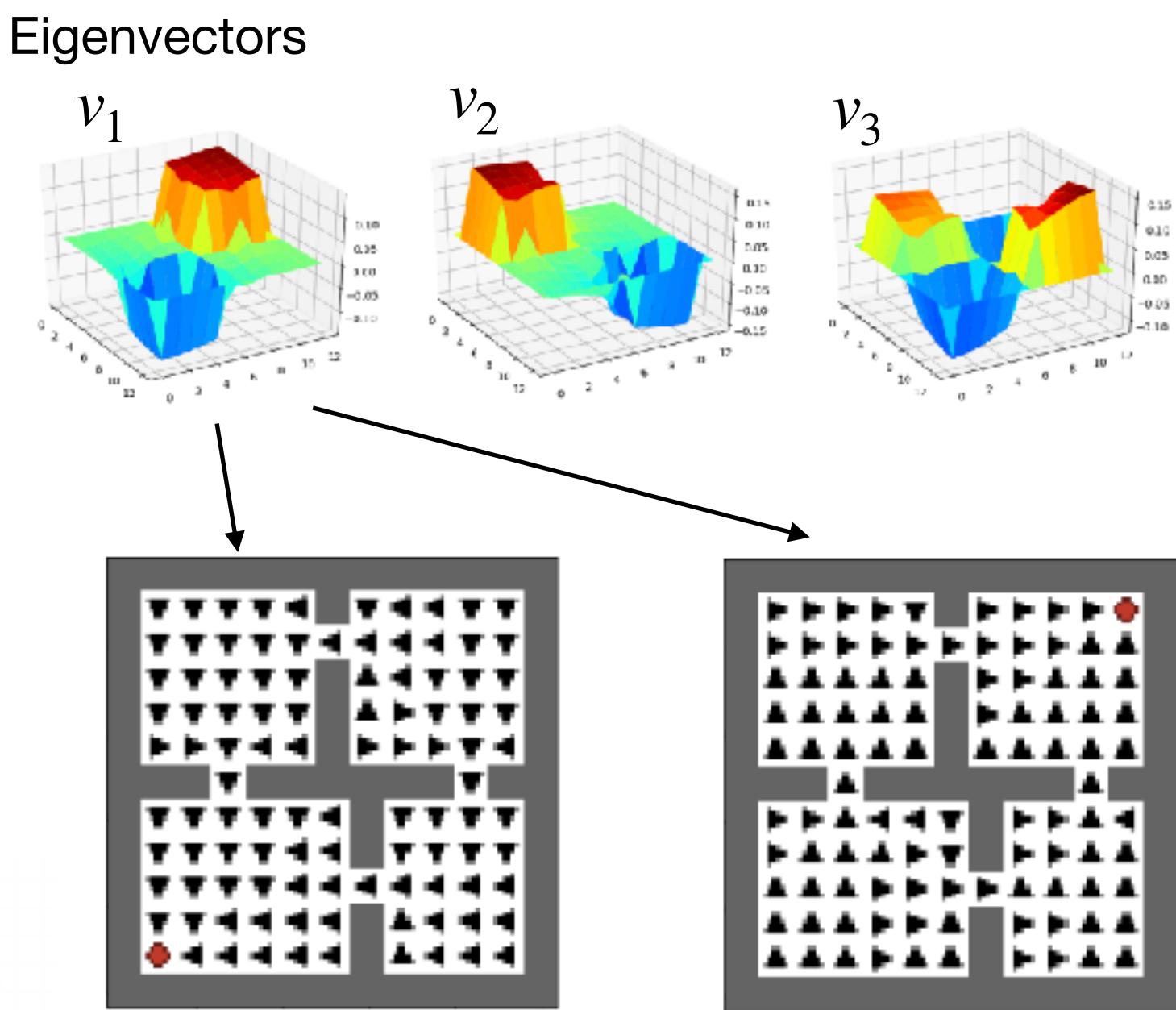
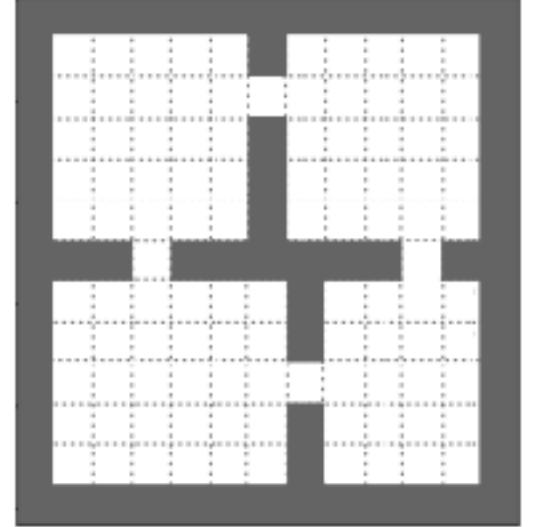
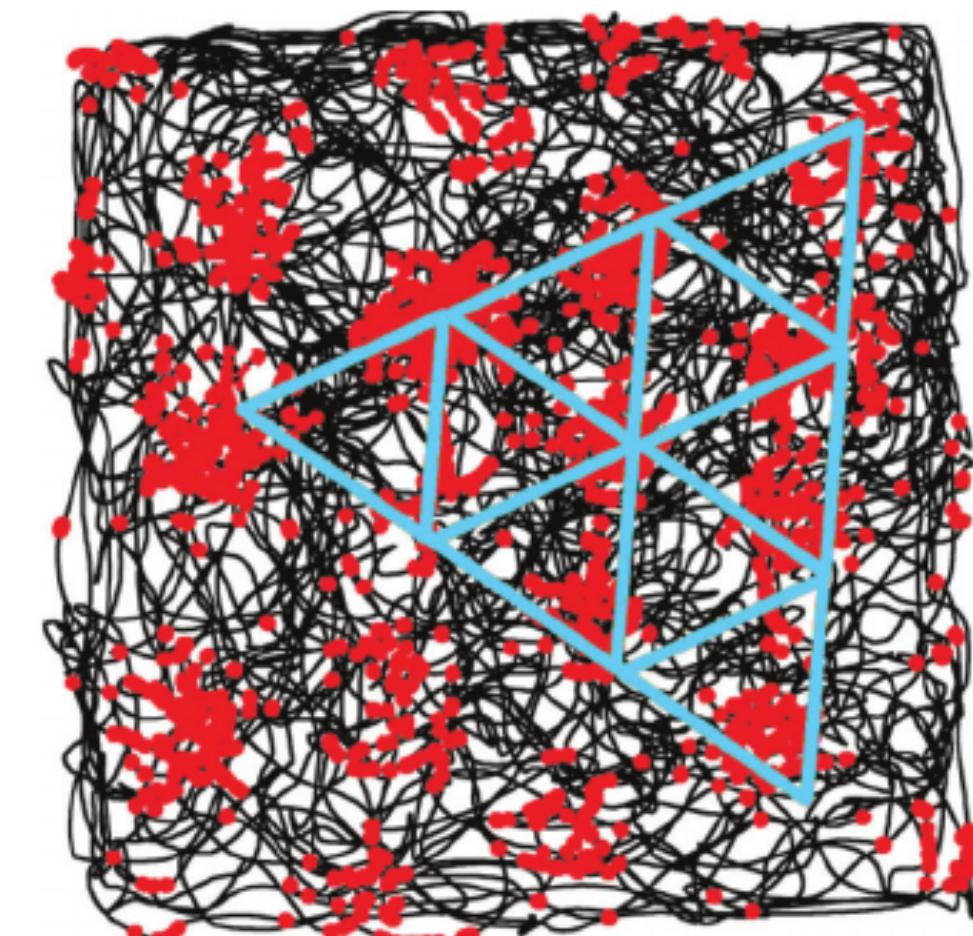
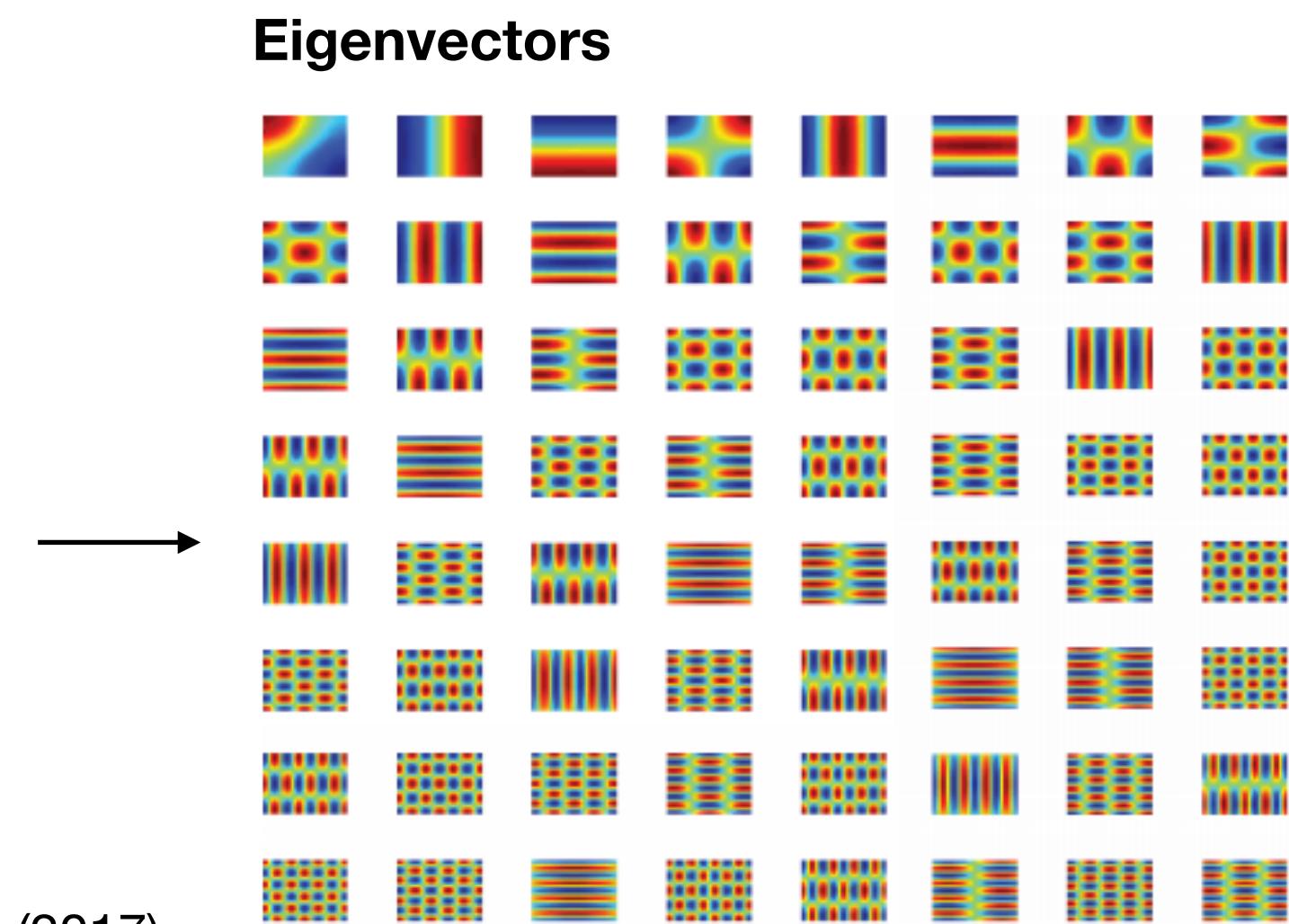
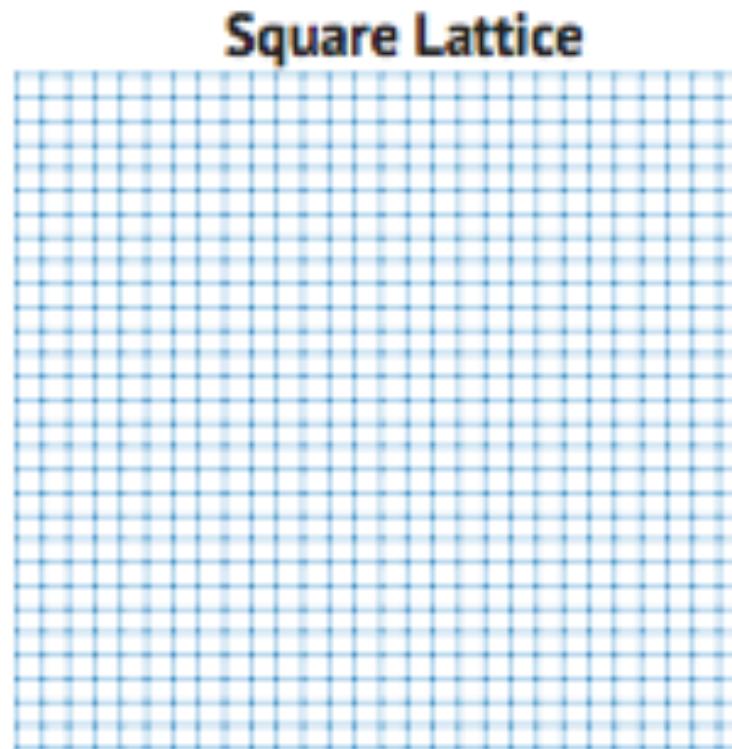
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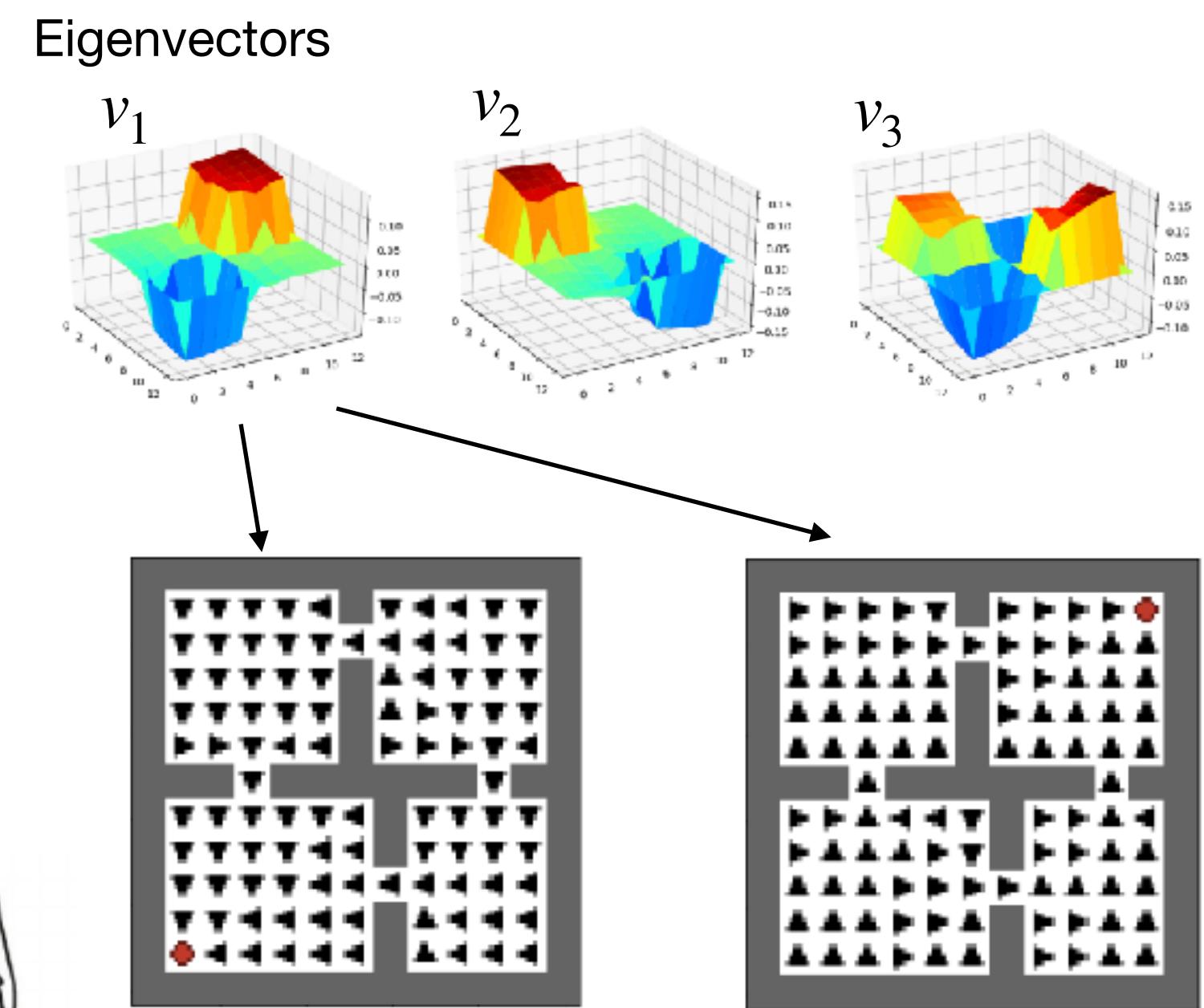
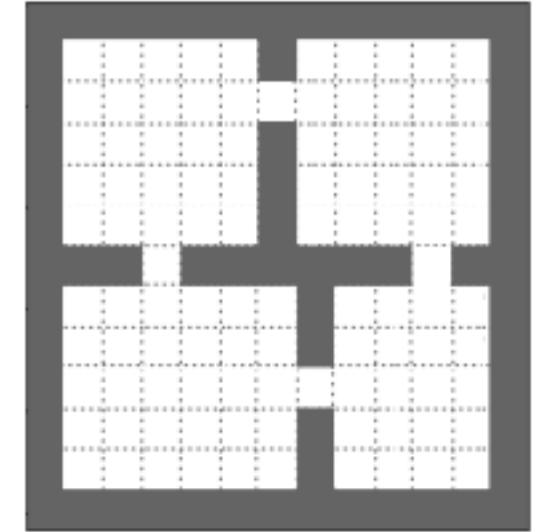
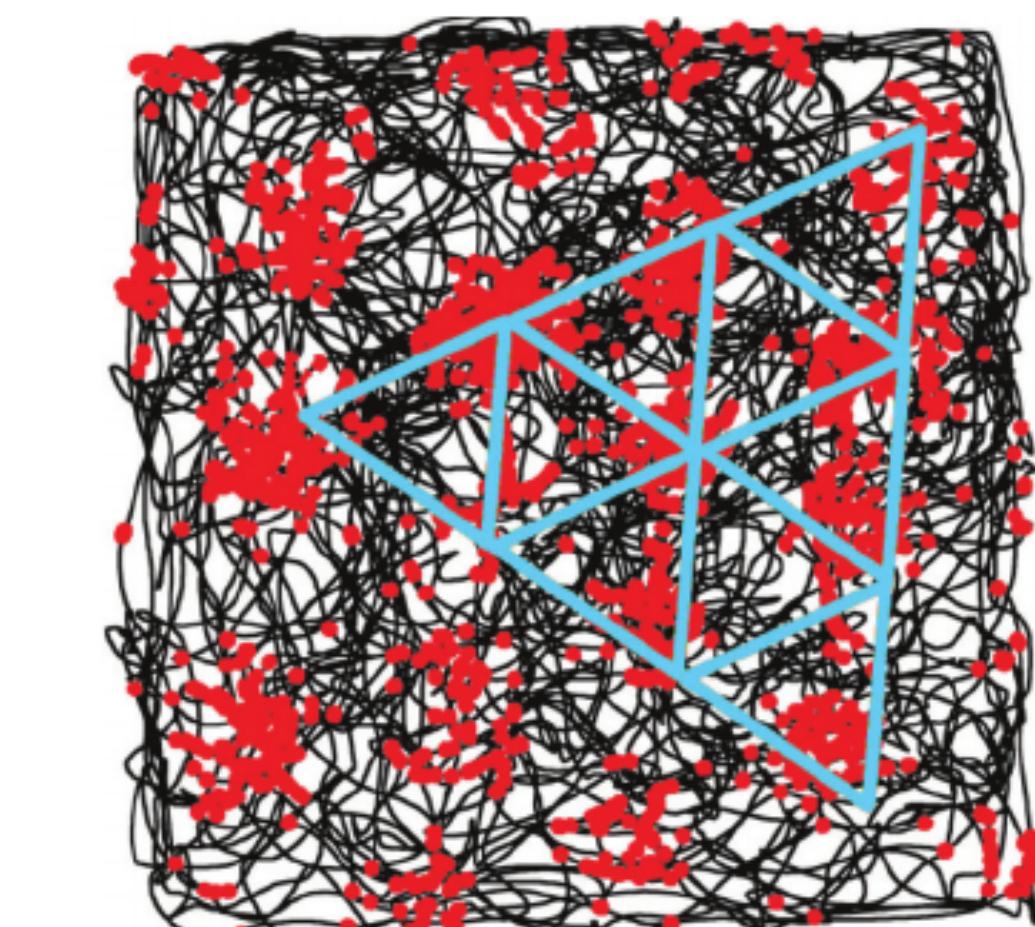
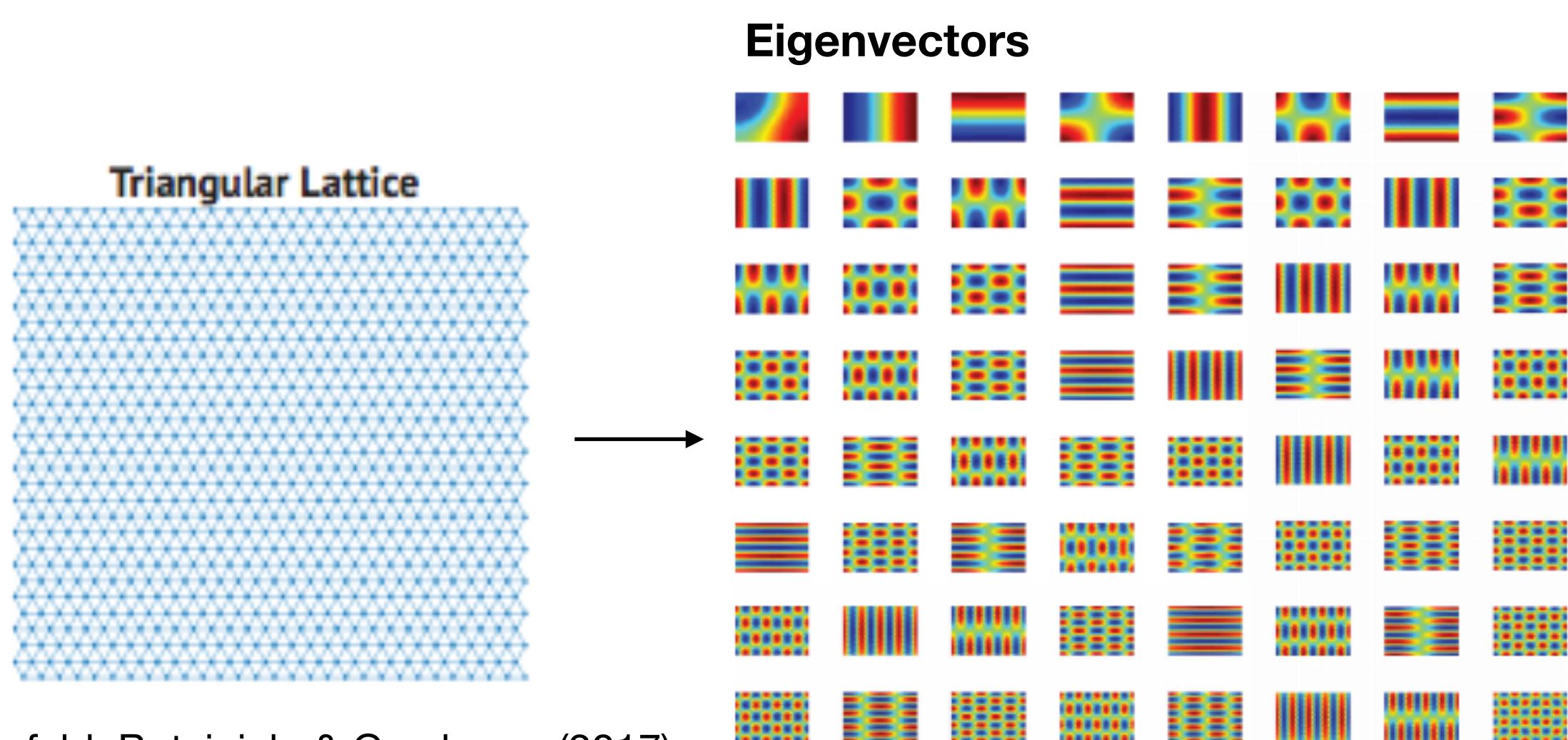
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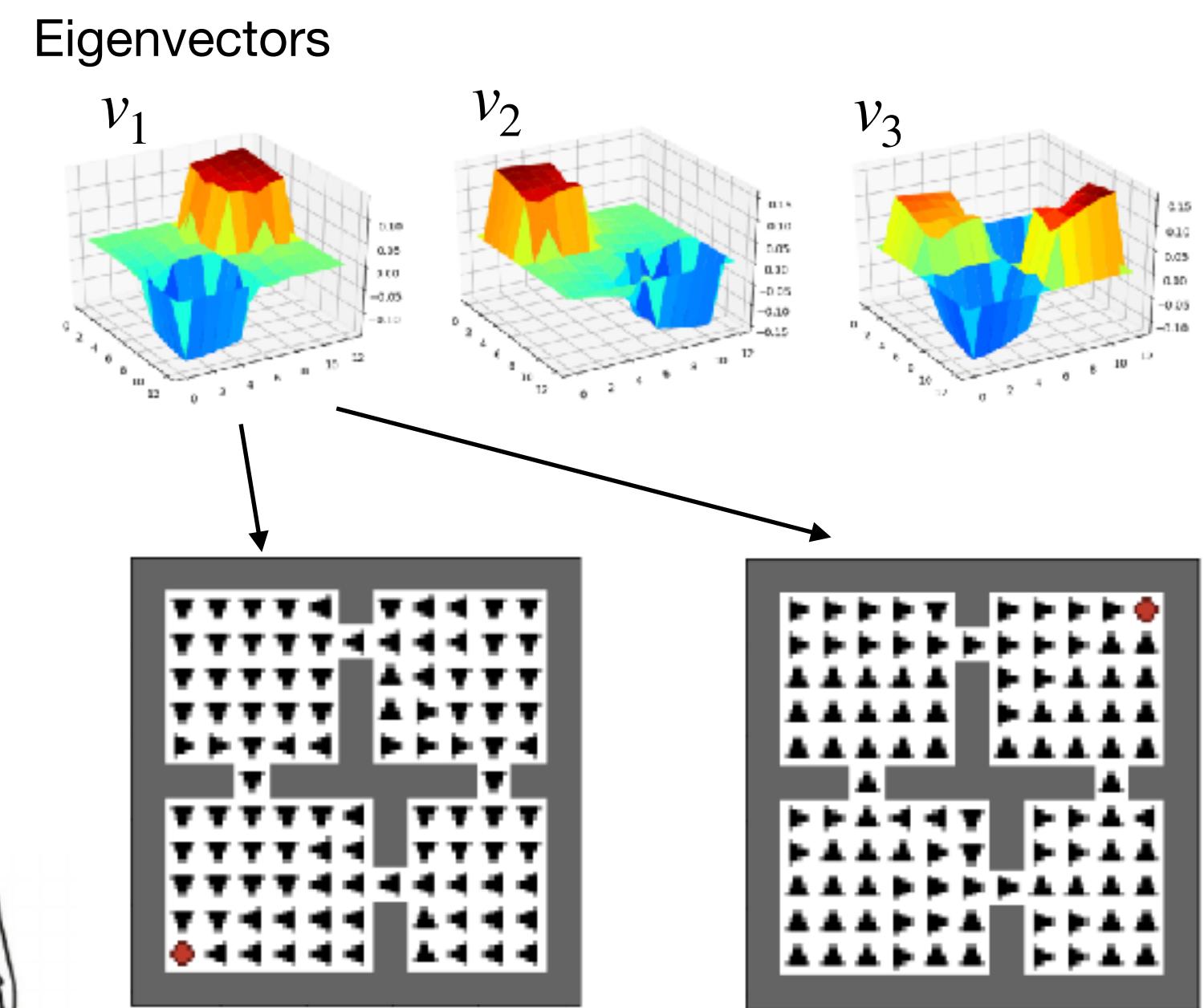
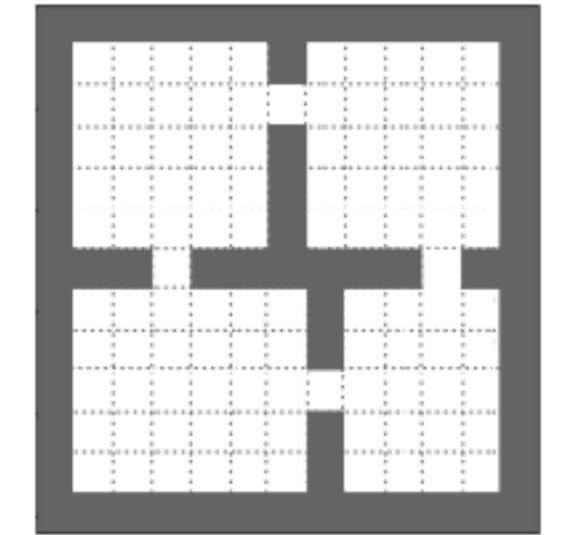
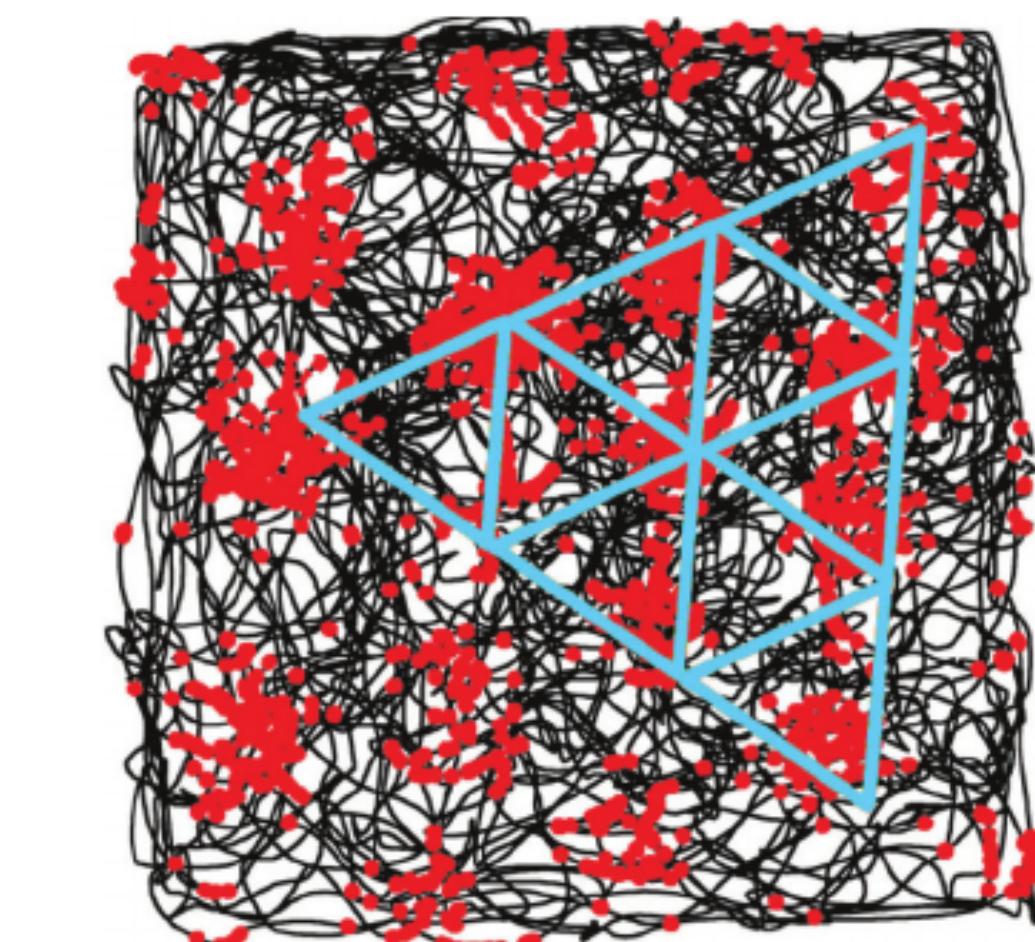
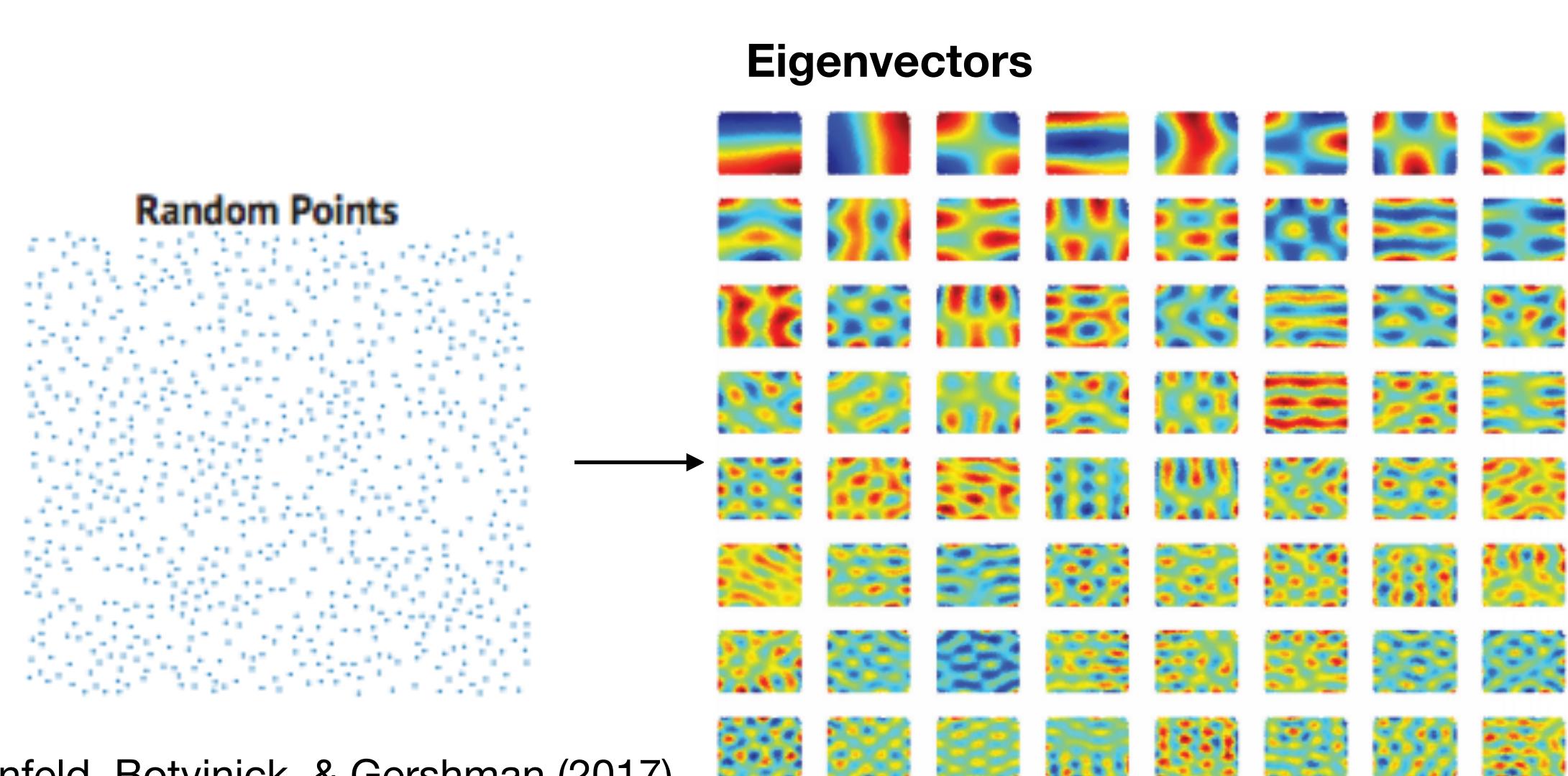
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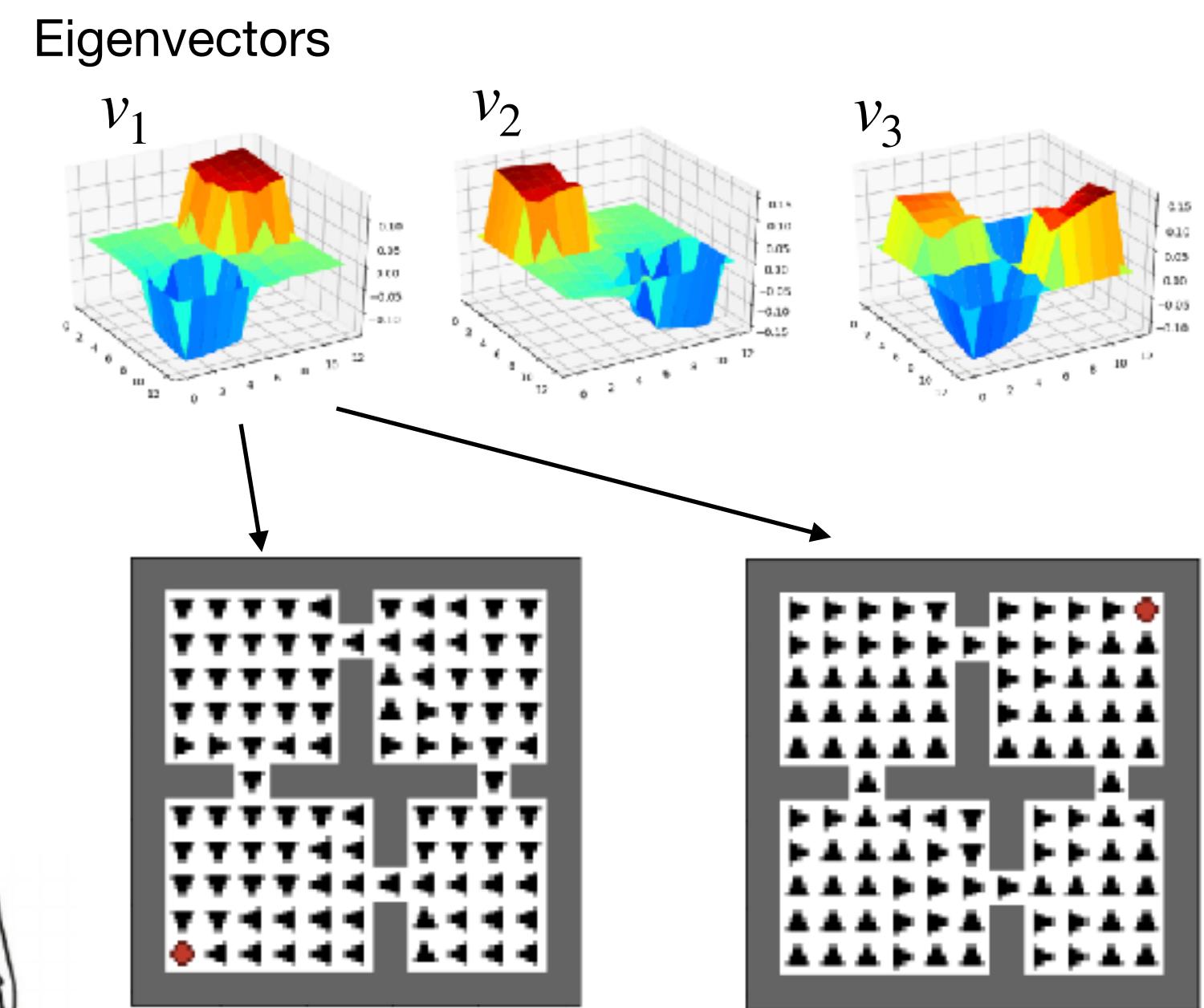
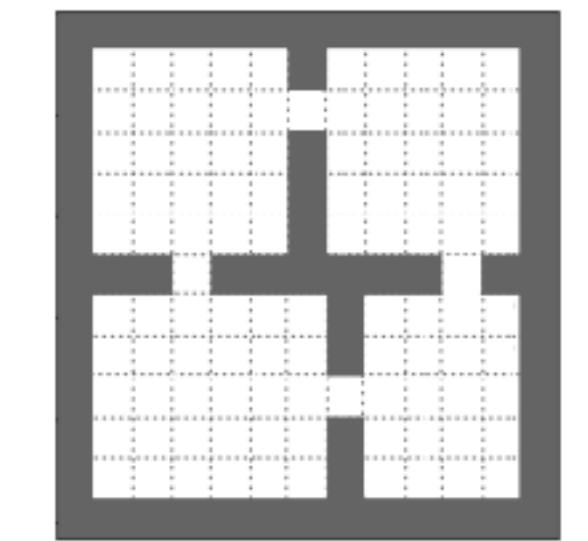
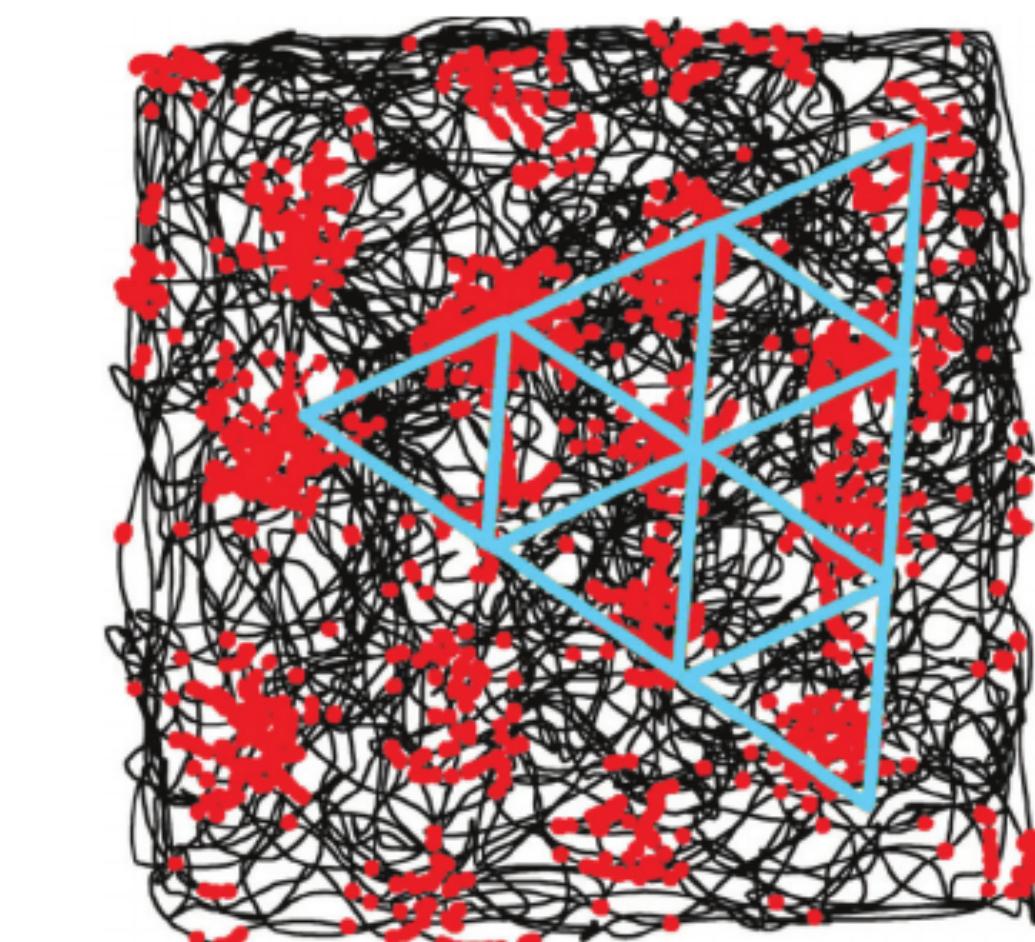
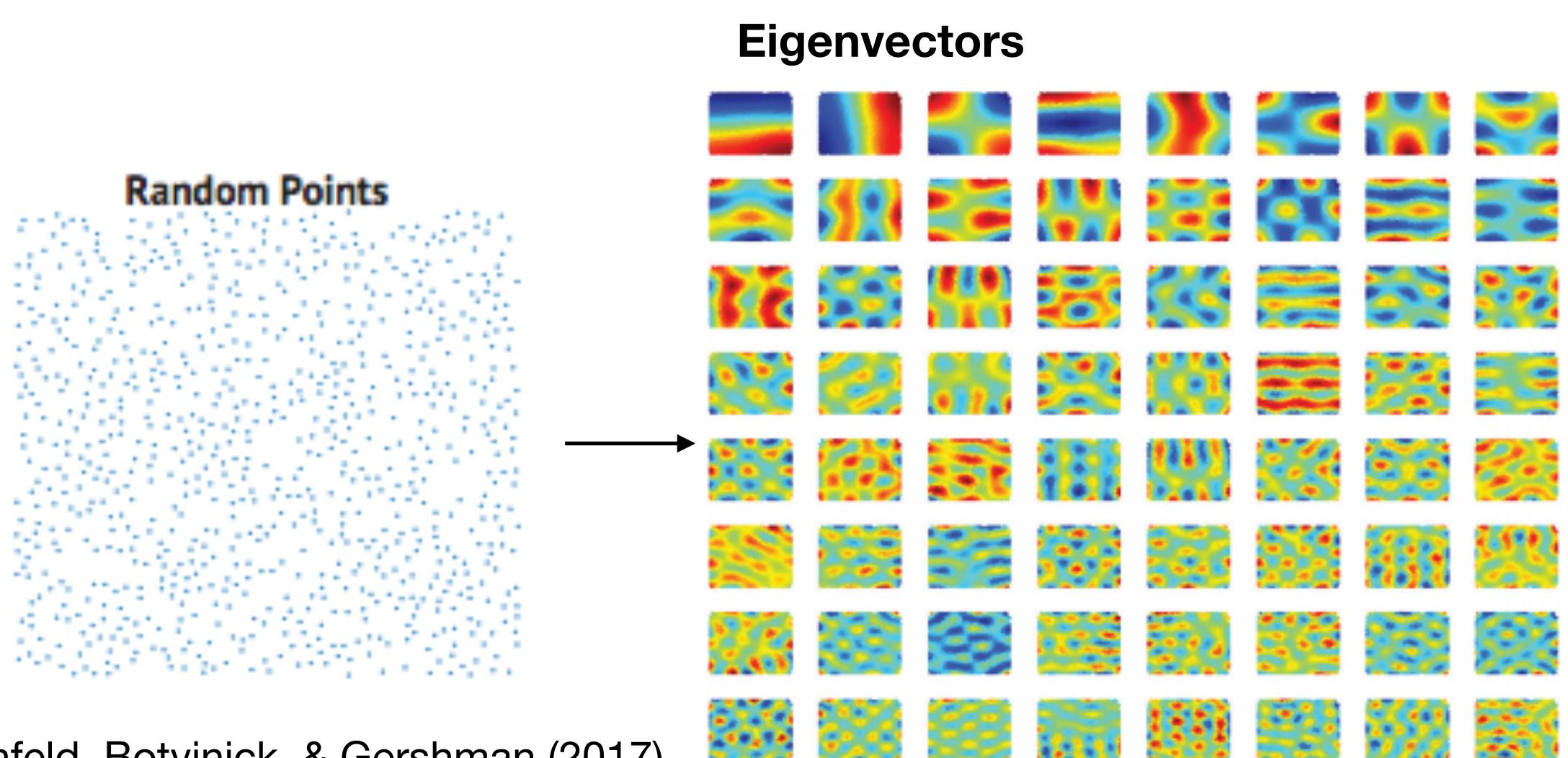
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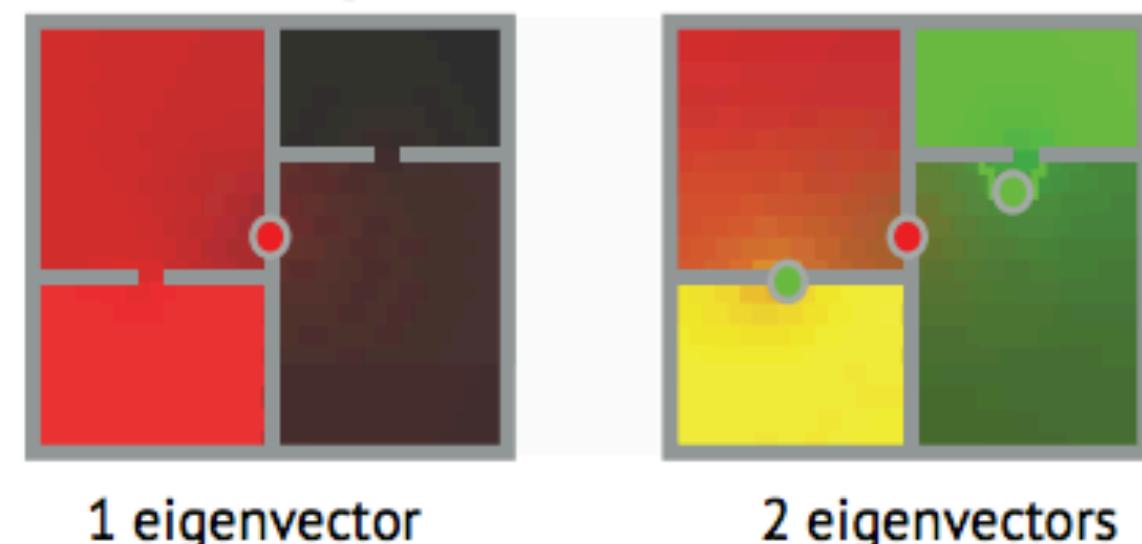
* Not unique to the SR, but any similarity metric that captures transition structure

SR naturally identifies subgoals

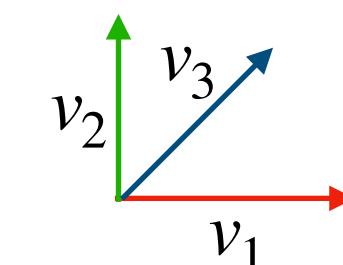
- Eigenvectors capture subgoals (i.e., compartments in the environment)

Stachenfeld, Botvinick, & Gershman (*NatNeuro* 2017)

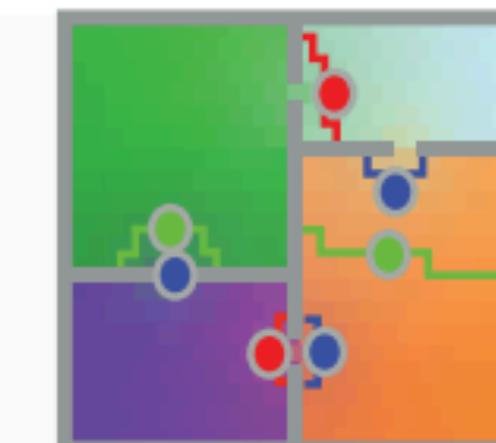
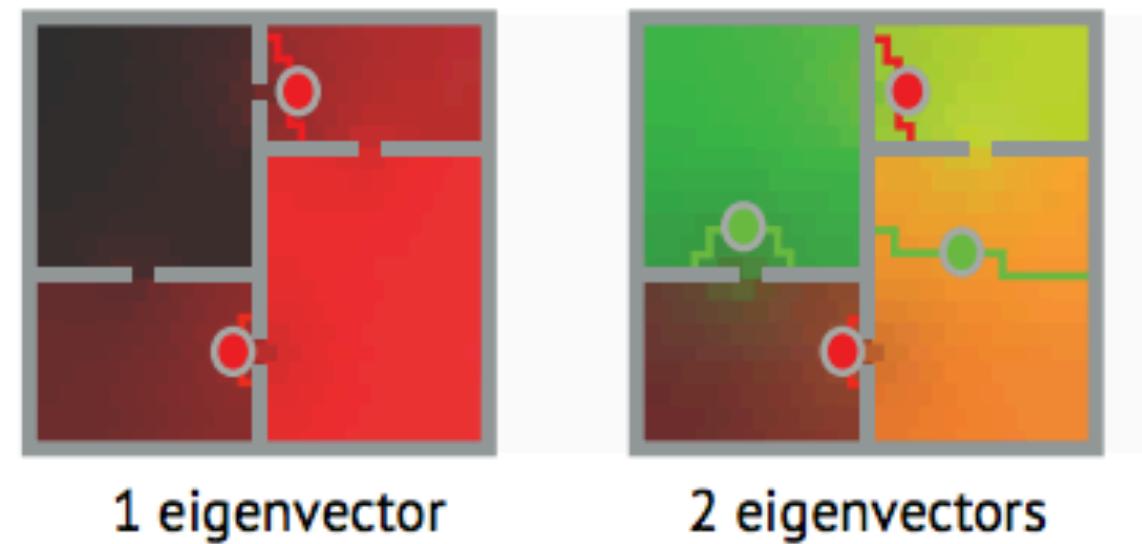
A Multi-compartment environment I



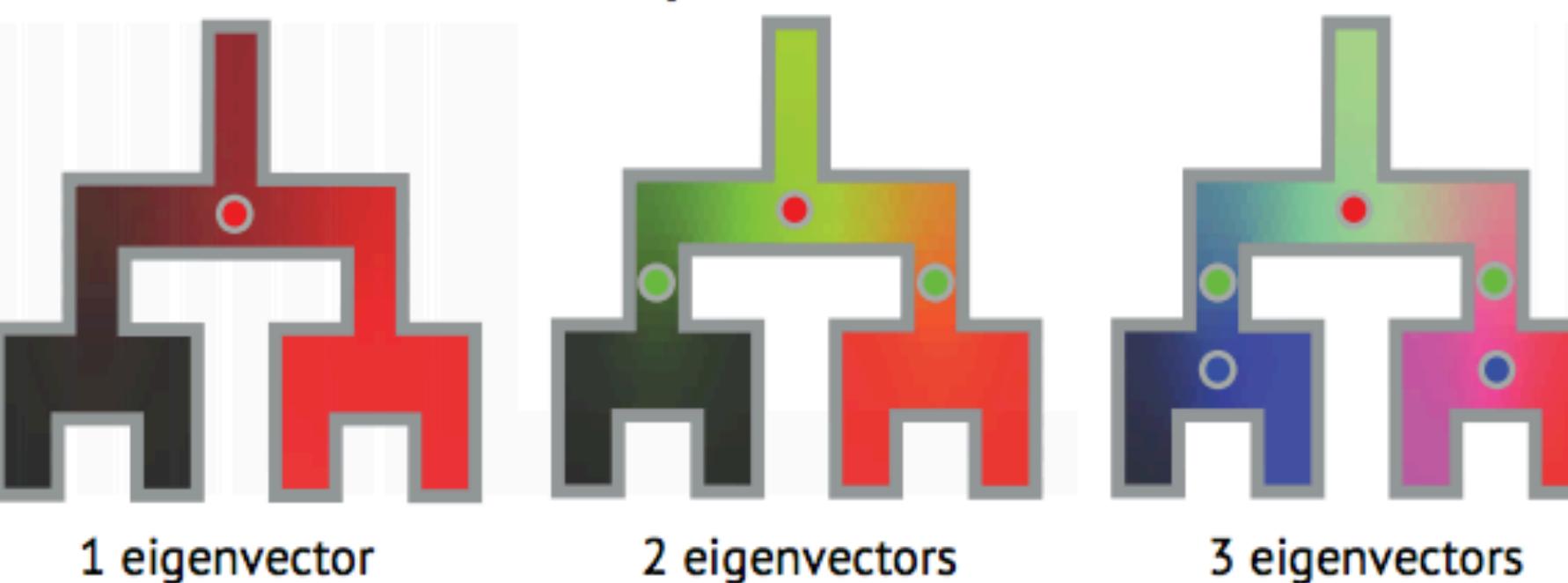
Subgoals
● 1-way partition
● 2-way partition
● 3-way partition



B Multi-compartment environment II

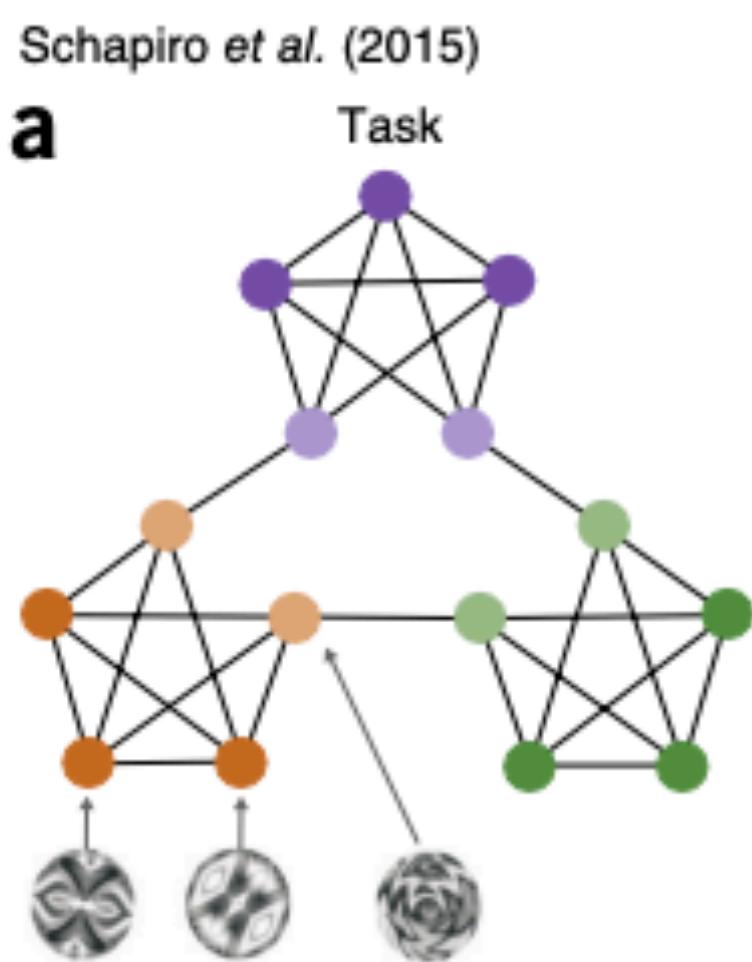


C Normalized cuts on 2-step tree maze

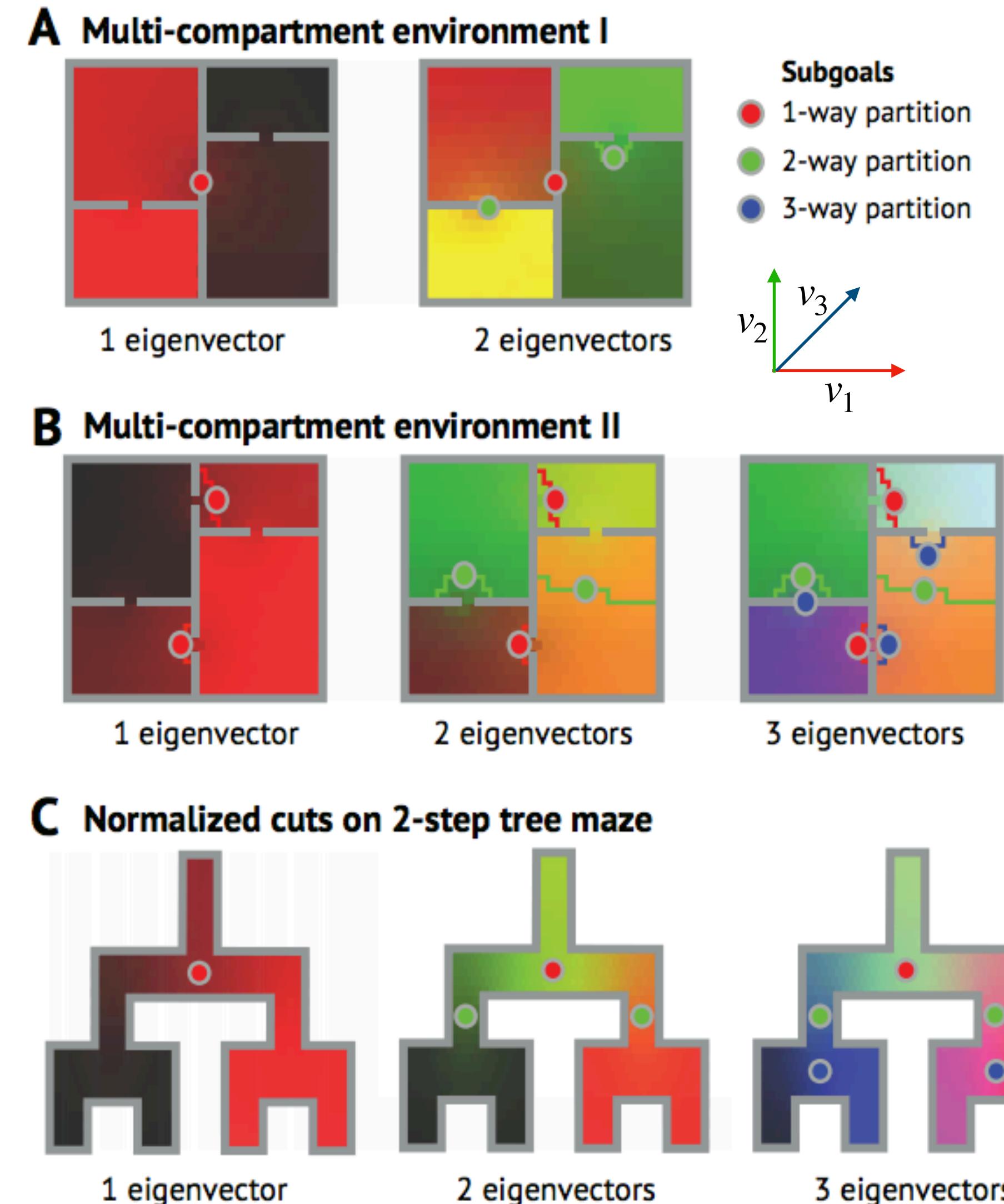


SR naturally identifies subgoals

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- These connectivity-based representations correspond to Hippocampal activity found in Schapiro et al. (2015) and Garvert et al. (2017)

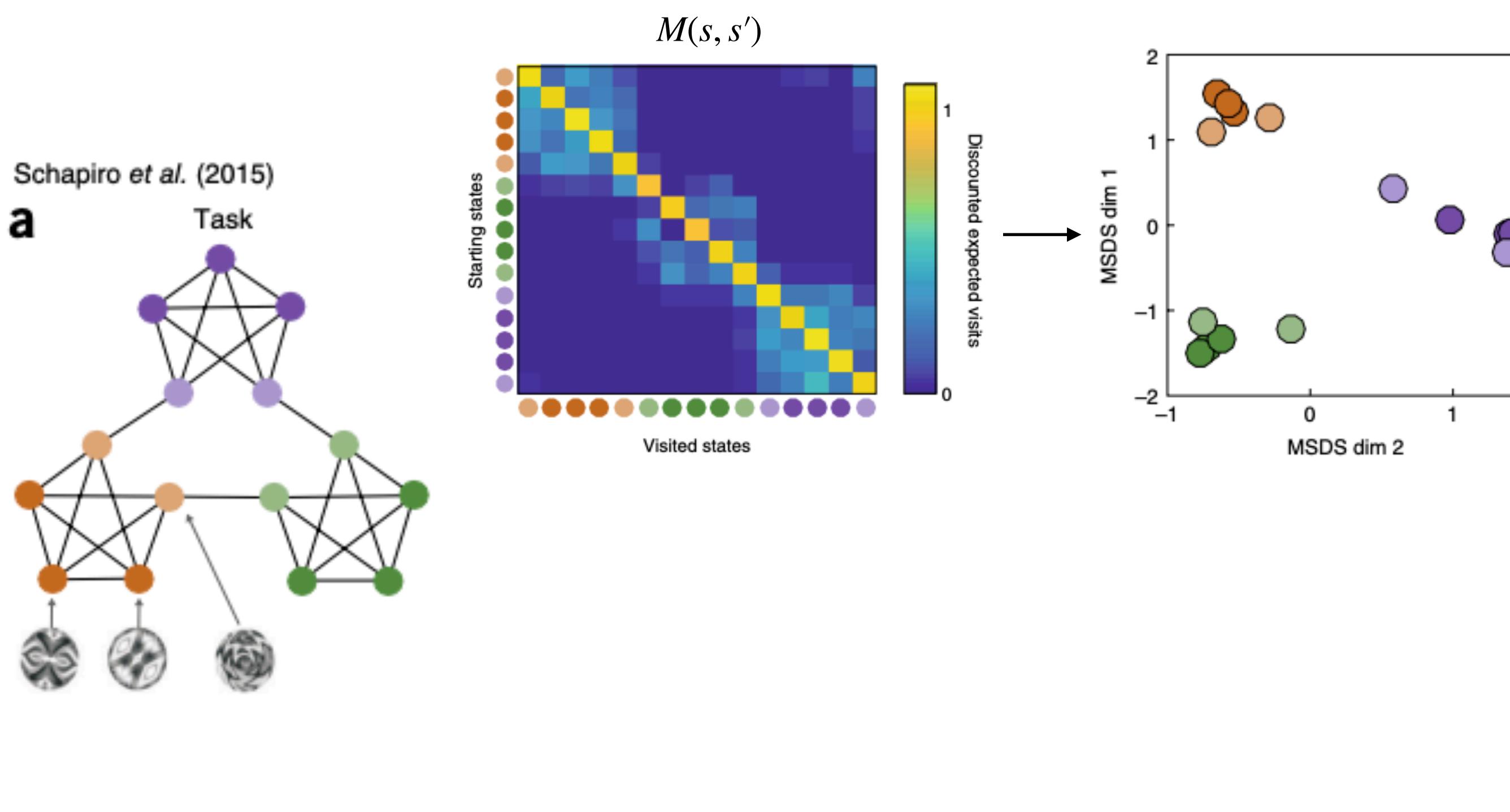


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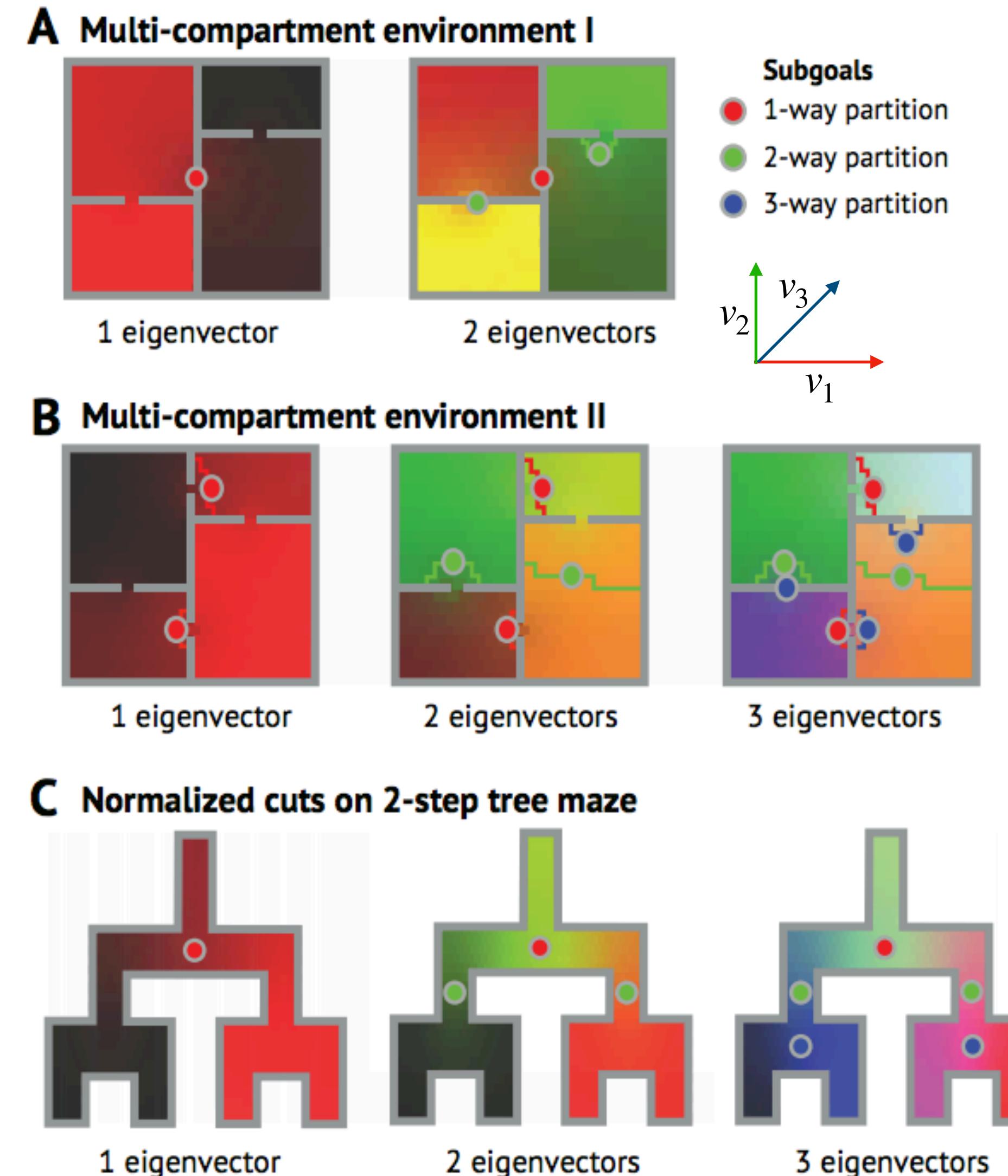


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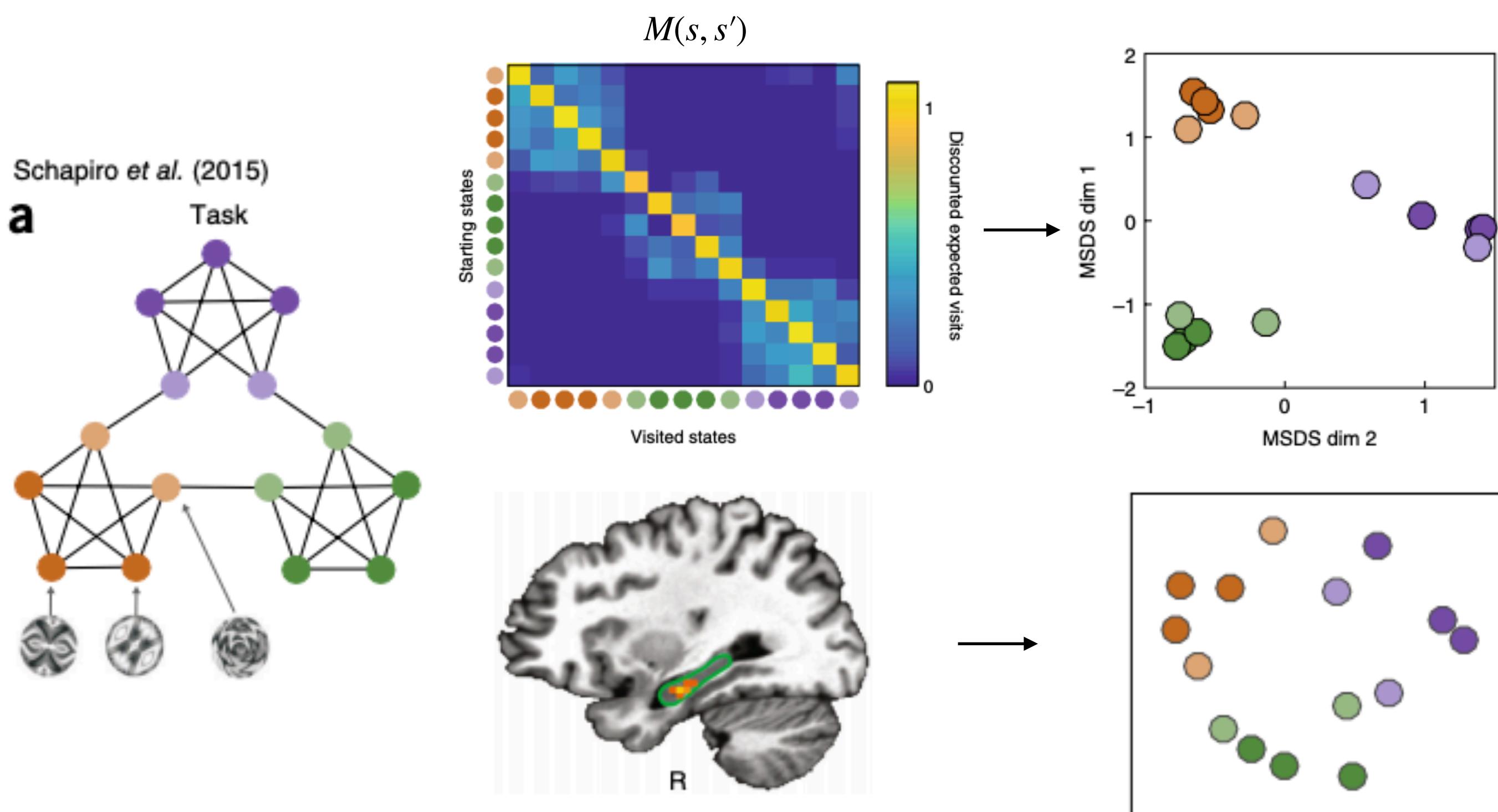


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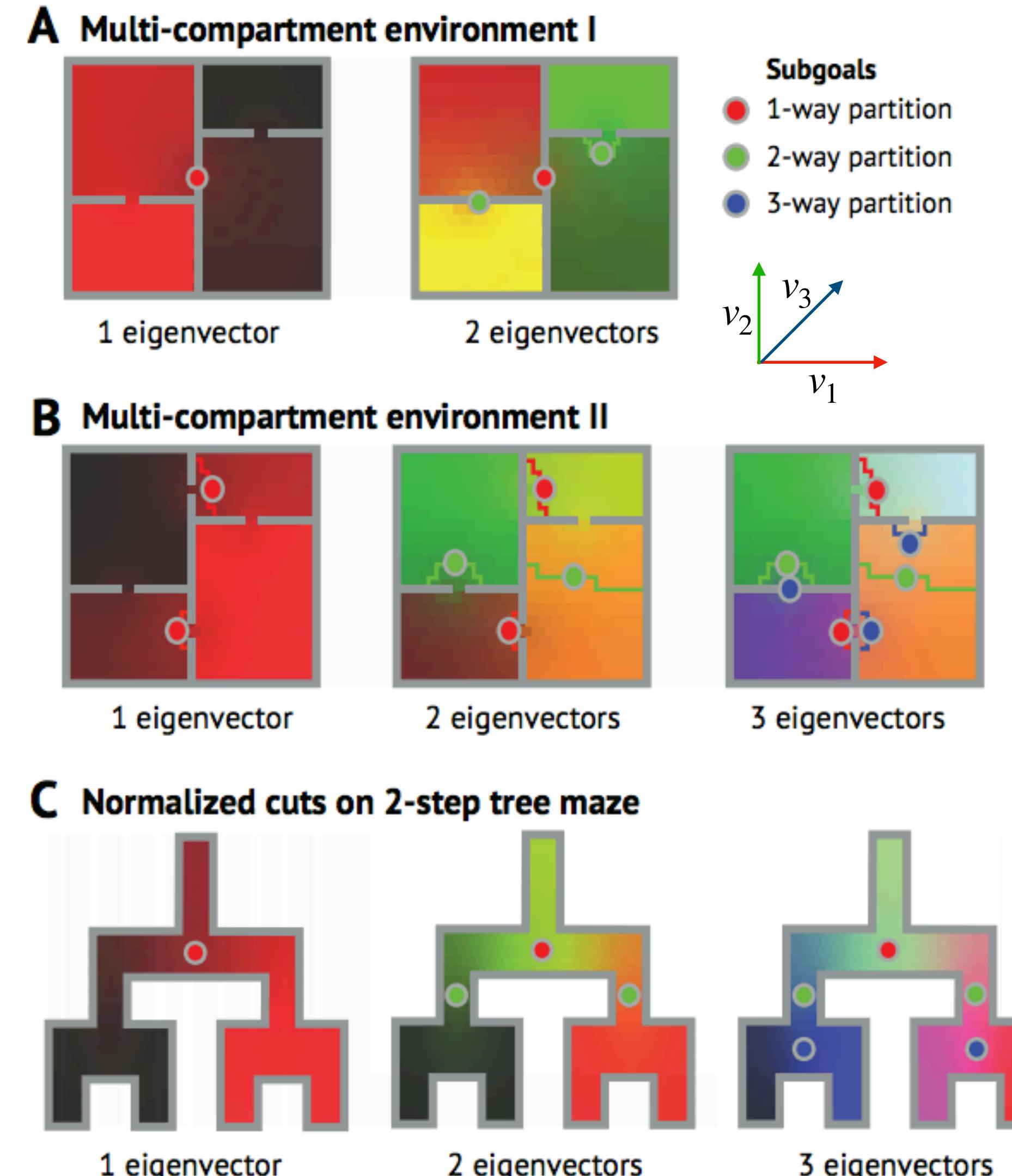


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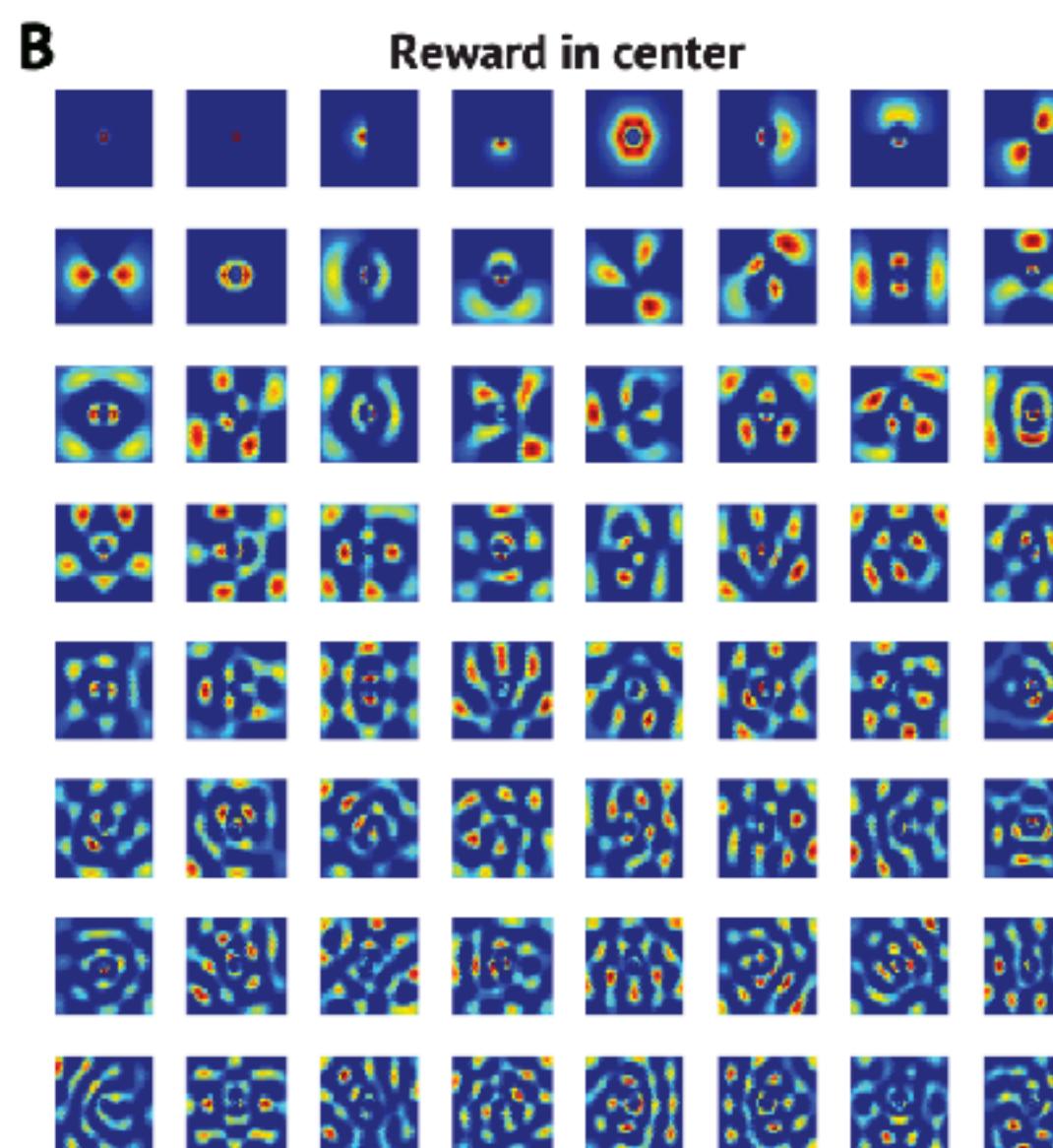
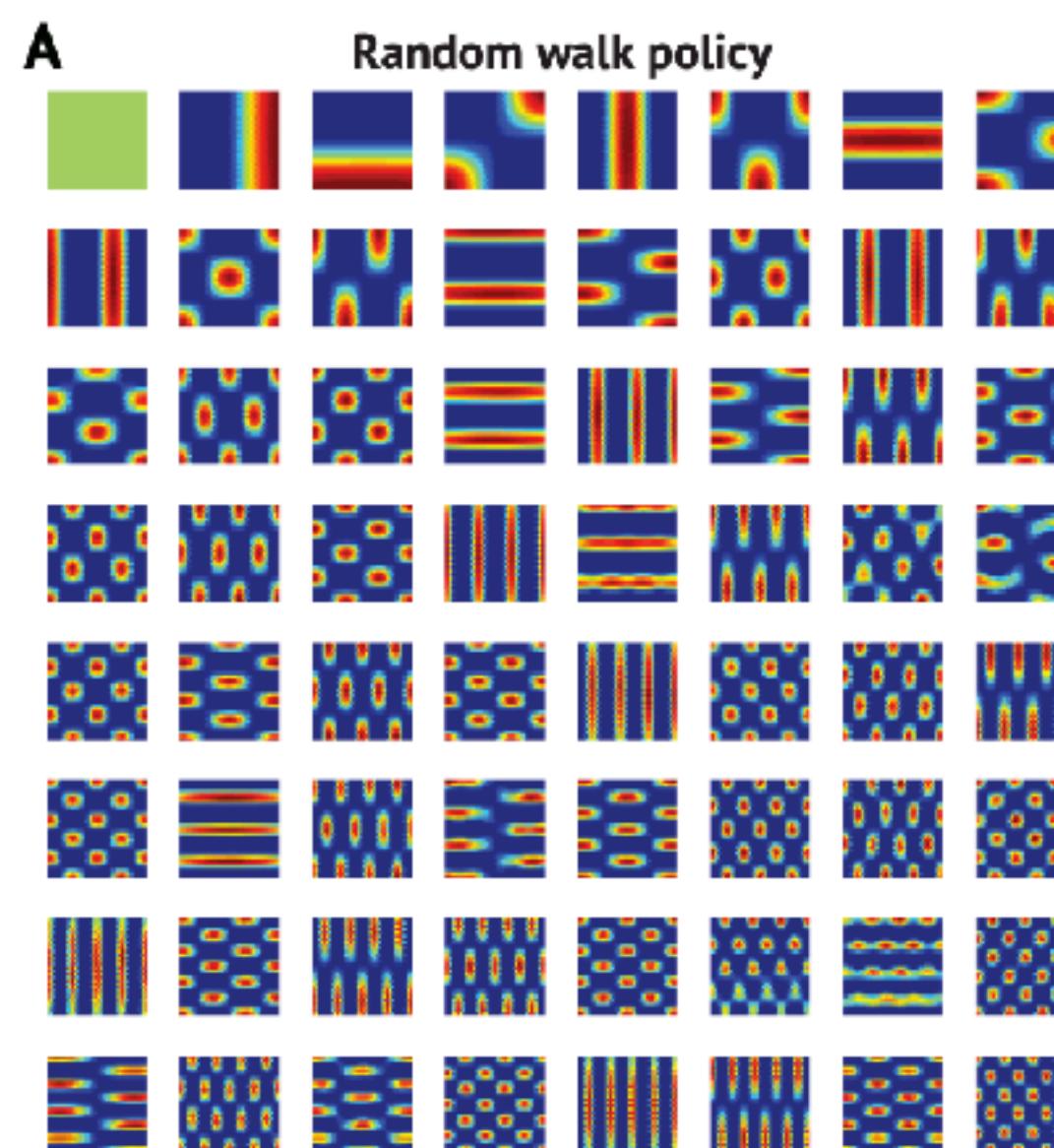


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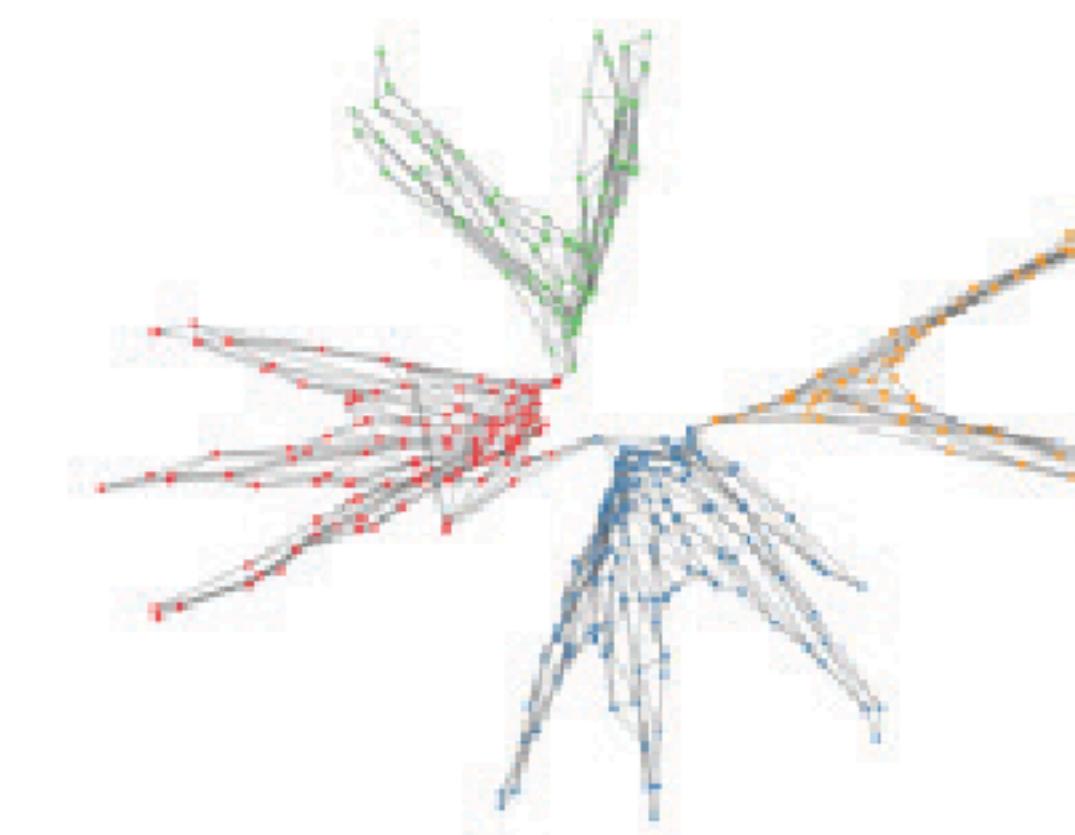


SR is sensitive to policy

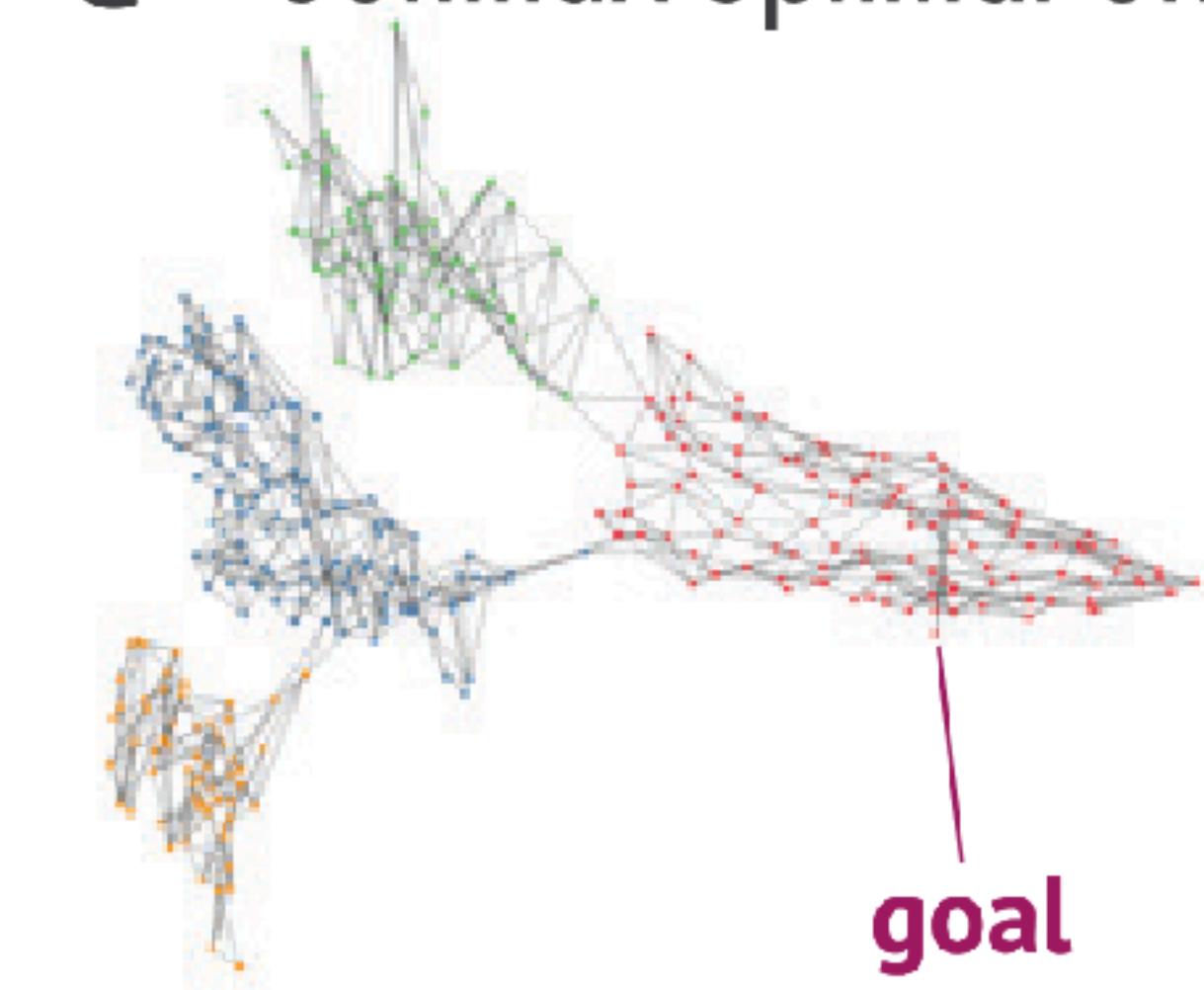
- SR learned under different policies learn different representations
- Under a softmax-optimal policy seeking the goal state, states become organized according to their distance from the goal
- But it also makes them less grid-like



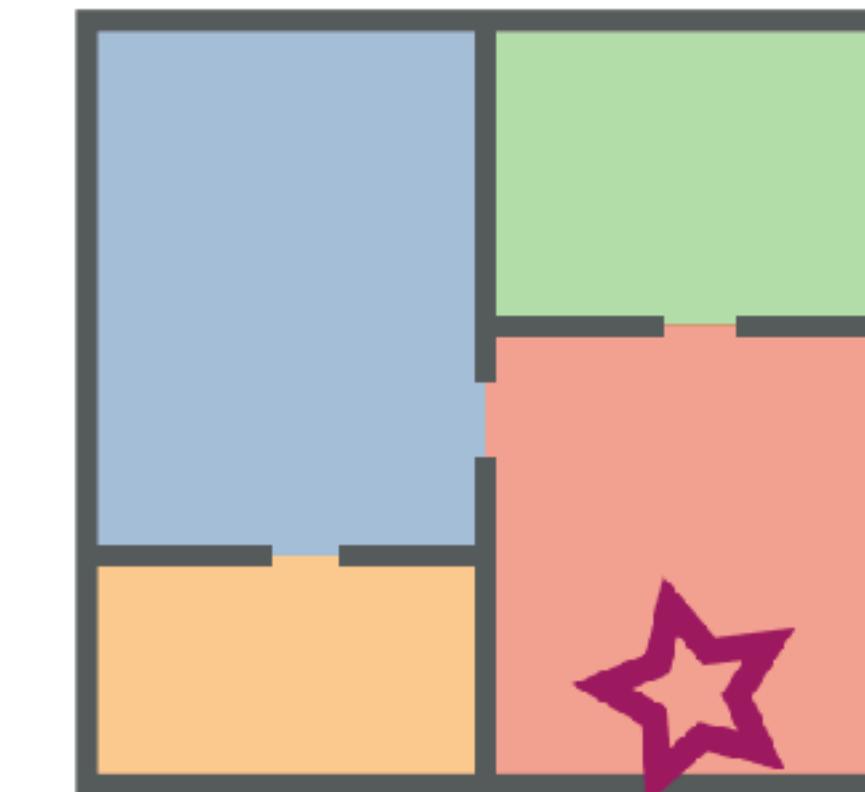
B Random walk SR



C Softmax-optimal SR



A Environment



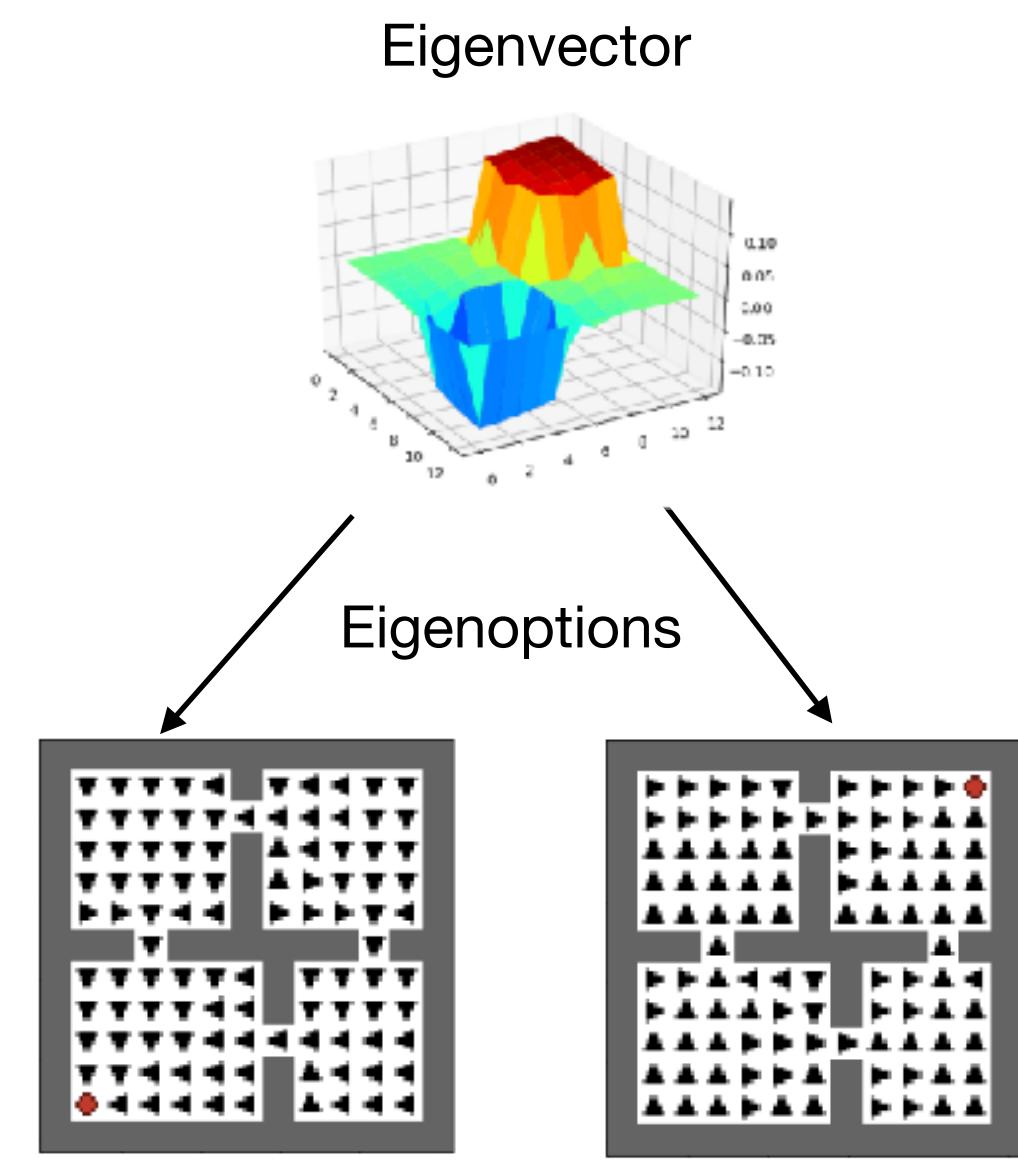
Stachenfeld (Phd thesis, 2018)

SR for option discovery

- “Options framework” in RL corresponds to learning extended sequences of actions instead of only a single action at a time
 - Options: Make coffee vs. make tea
 - Actions: move left leg, move right leg, move wrist 34 degrees
- SR naturally discovers *Eigenoptions*
- More recent work has identified functional sequences of actions this way

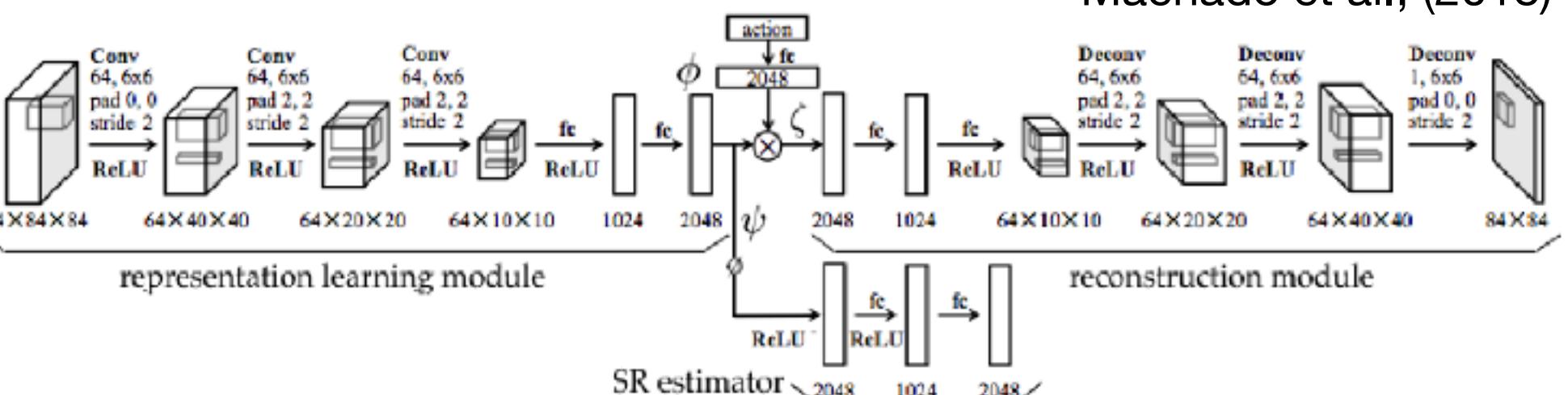
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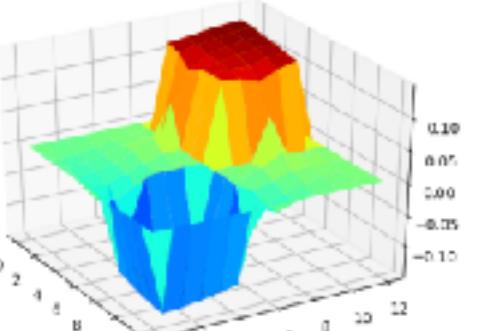


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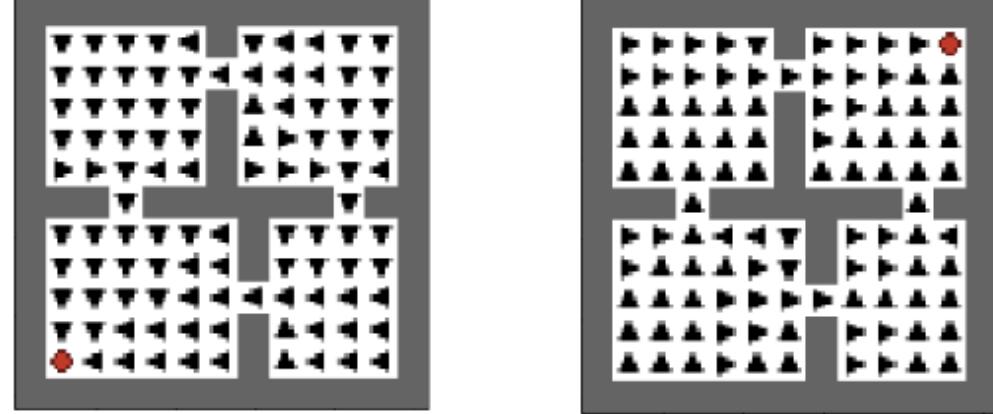
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Eigenvector



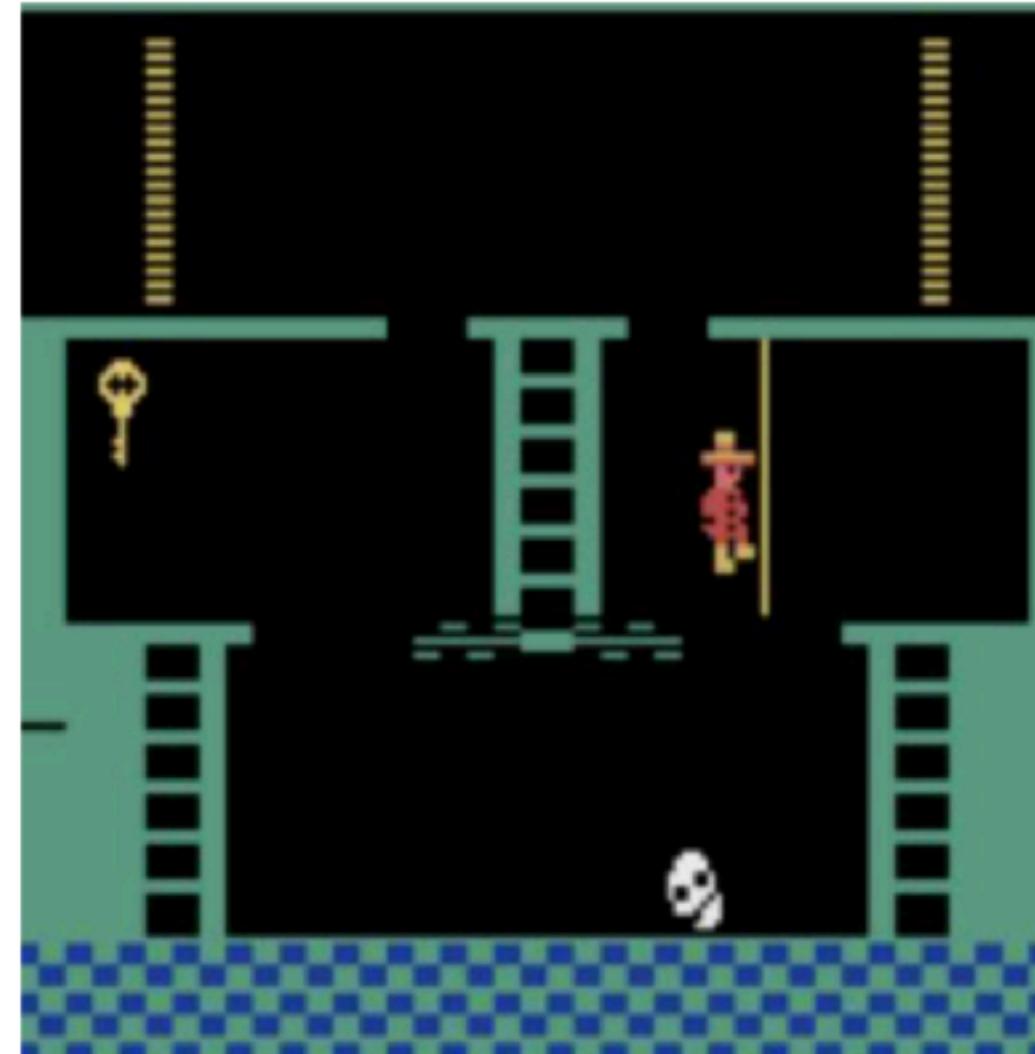
Eigenoptions



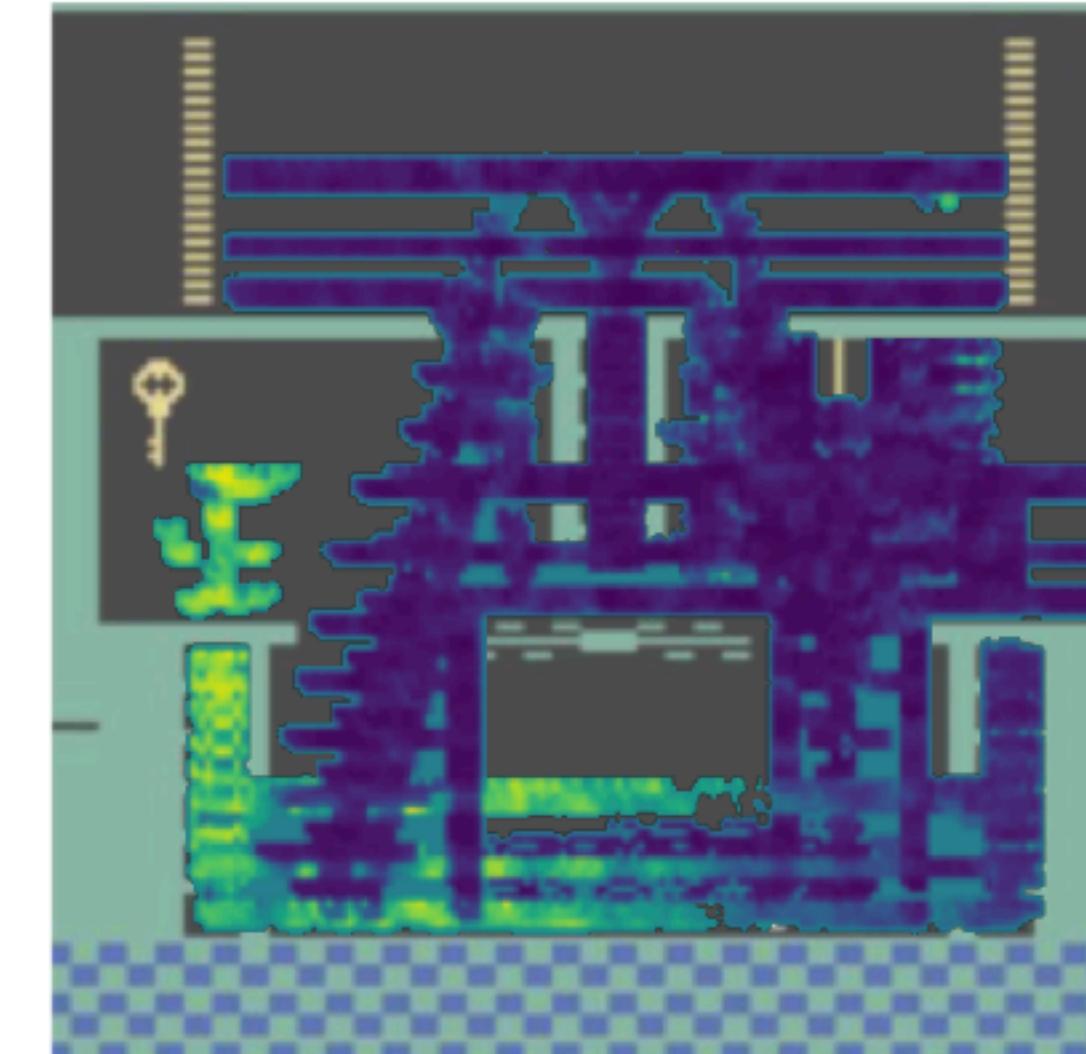
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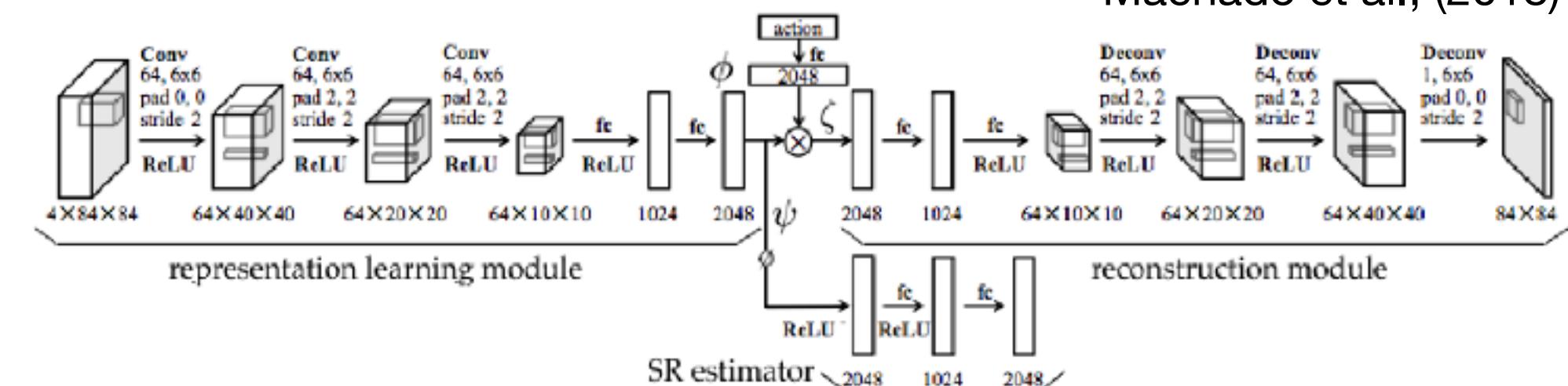
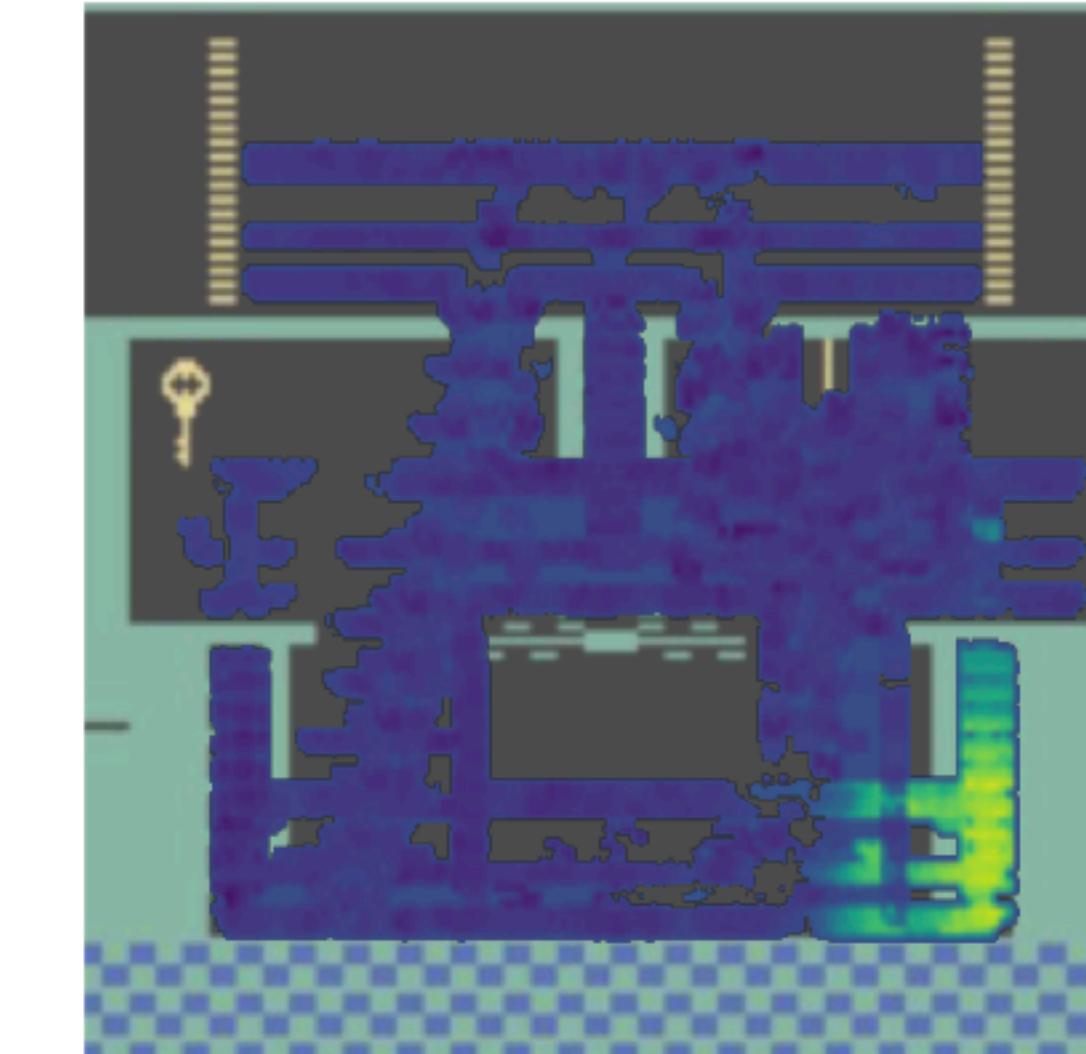
Montezuma’s Revenge



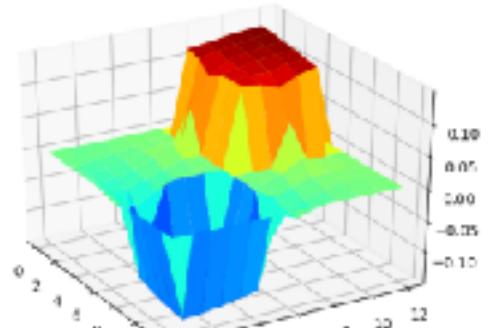
Eigenfunction #1



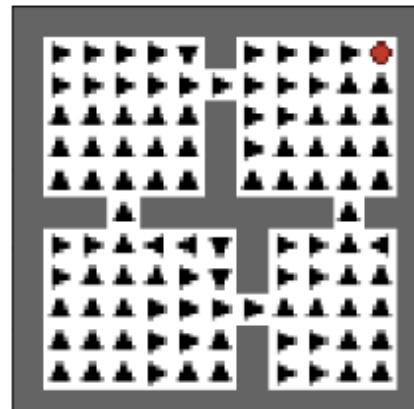
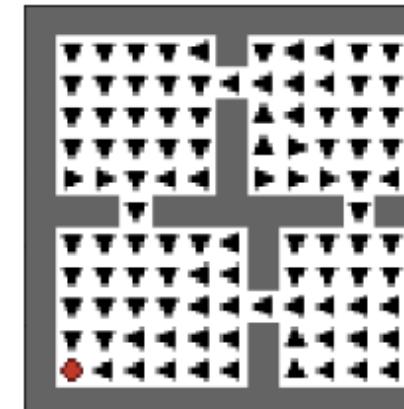
Eigenfunction #2



Eigenvector



Eigenoptions



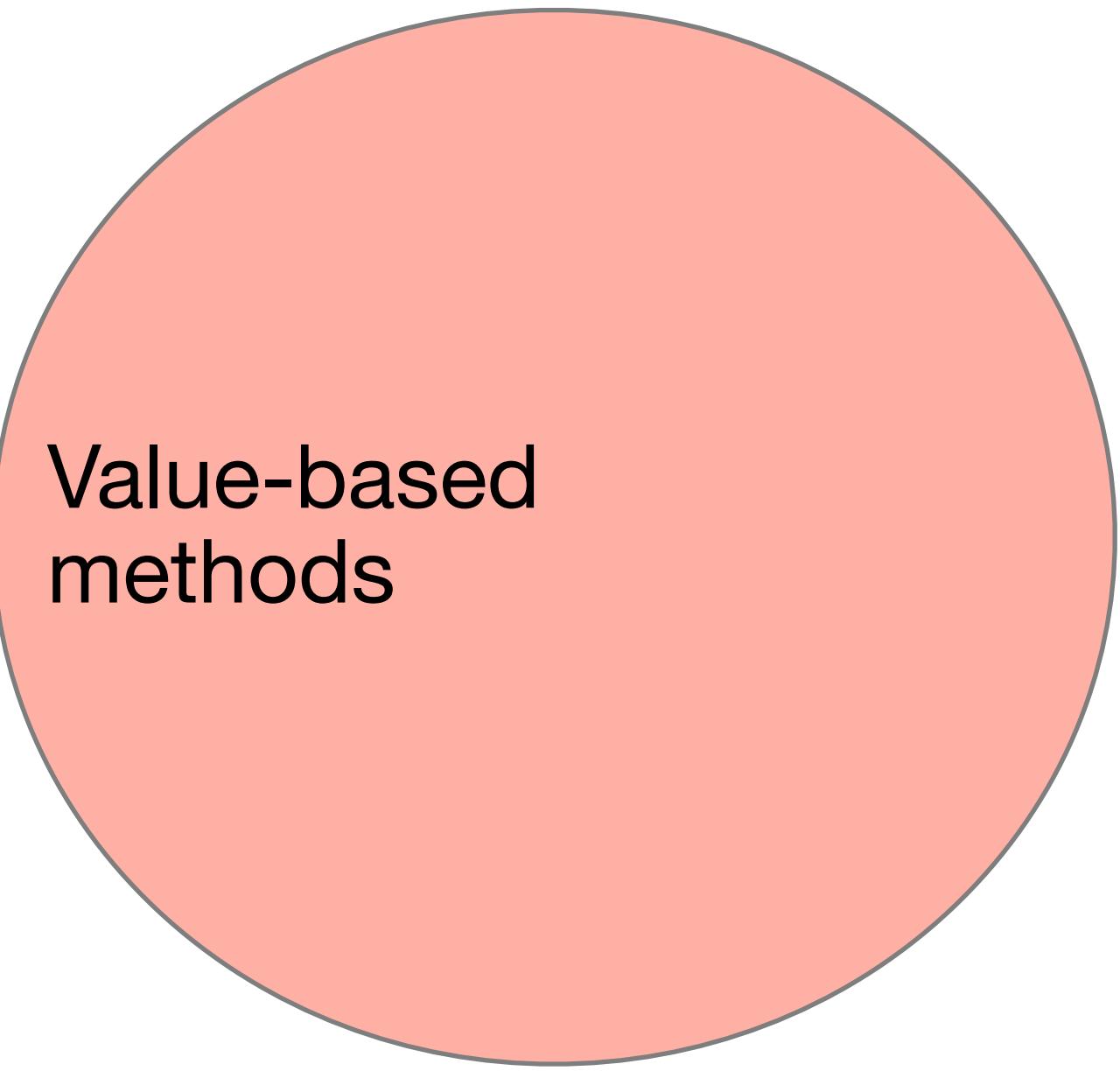
Summary

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 - **Value-based** Deep Q-Learning
 - **Policy-based** Policy Gradient
 - **Actor-Critic**

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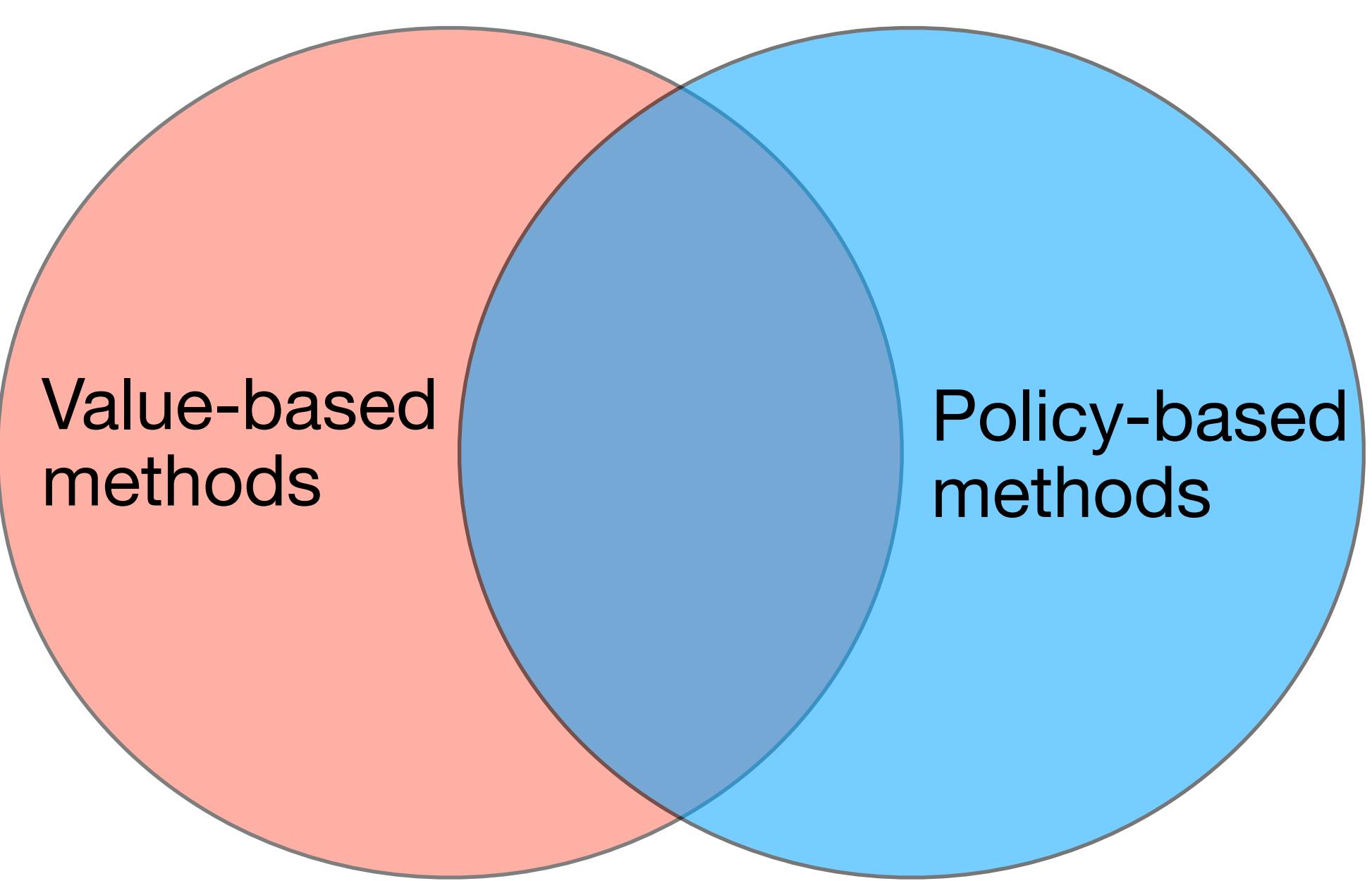
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Value-based
methods

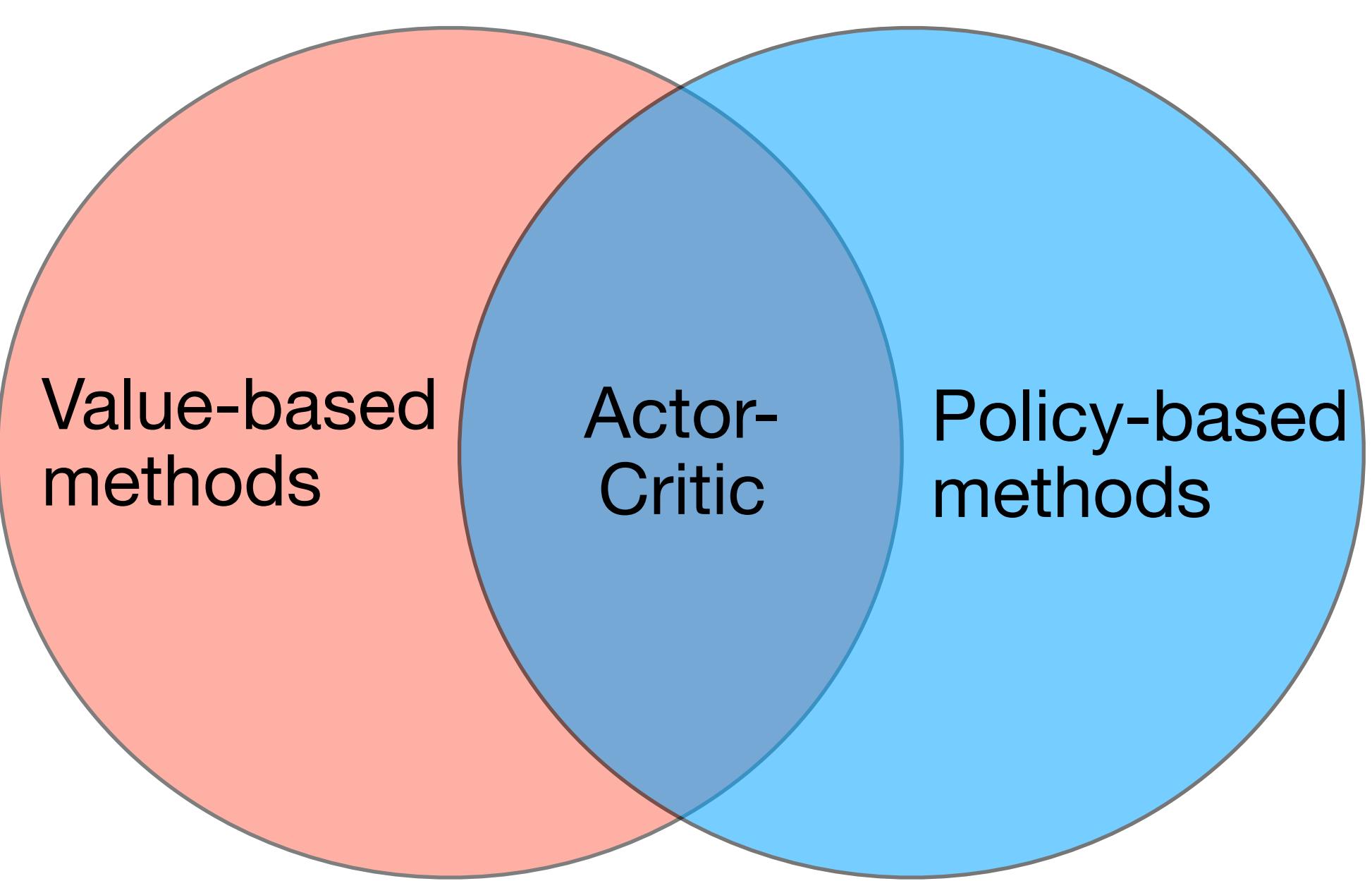
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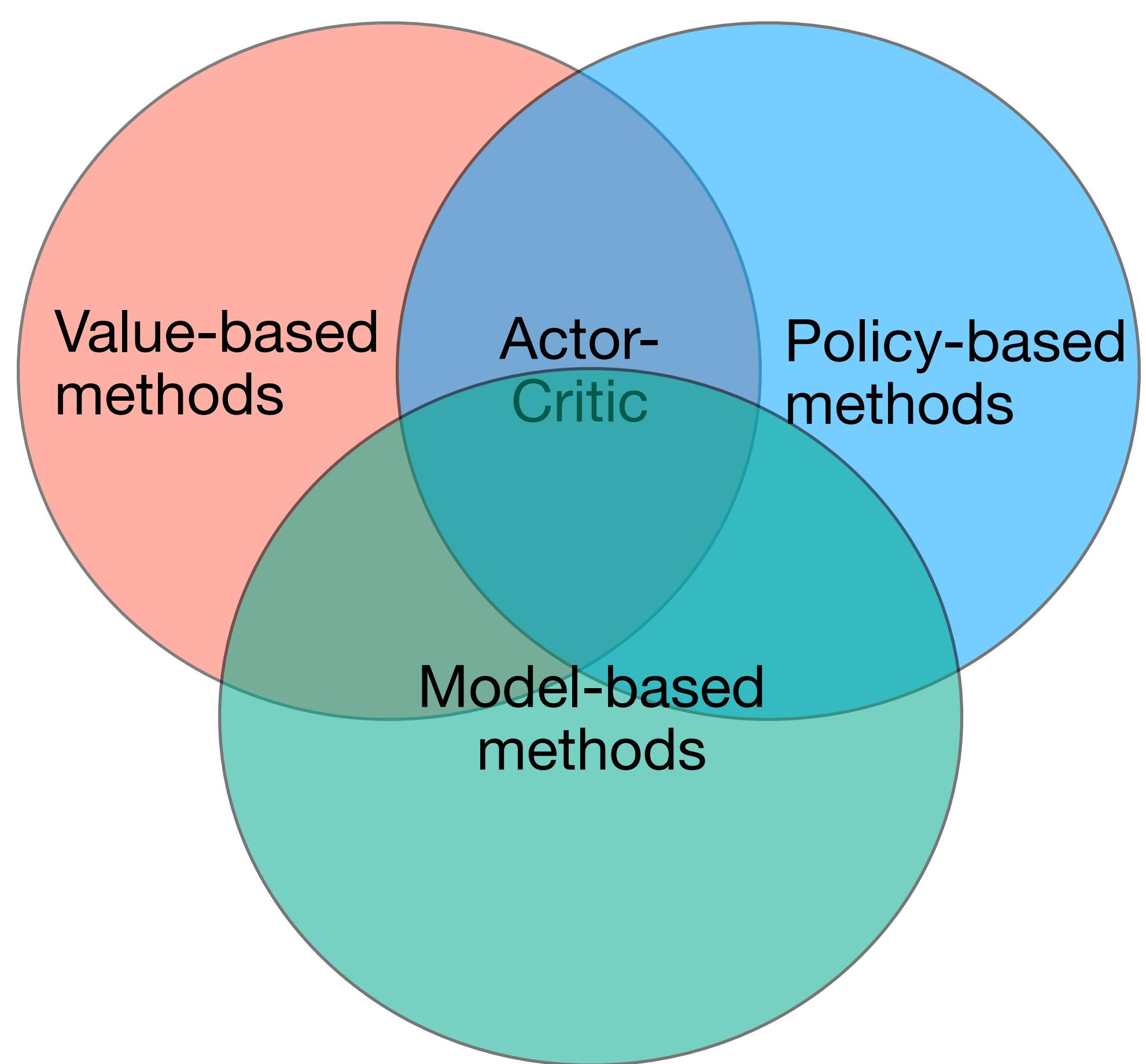
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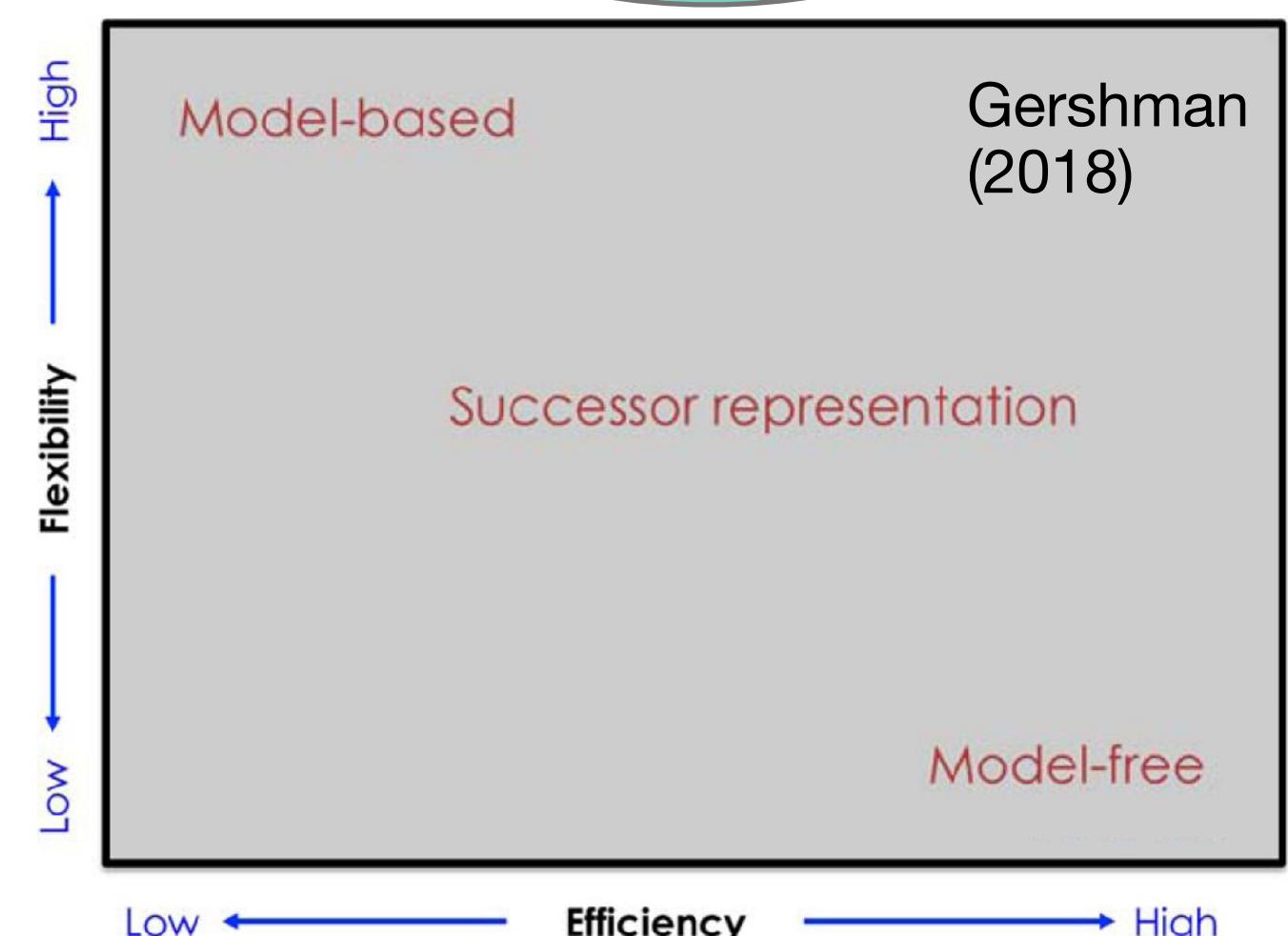
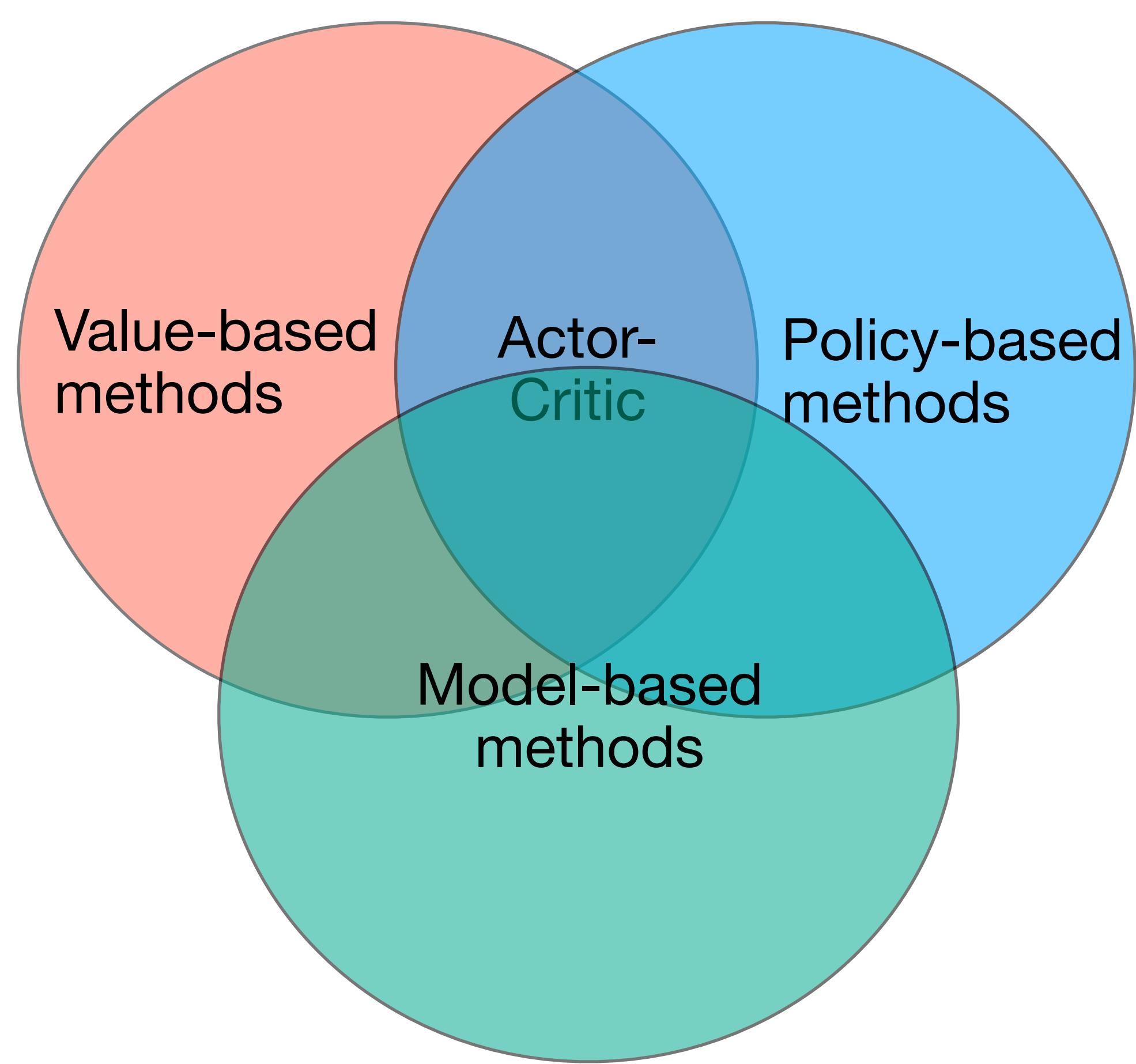
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 - Balancing flexibility and efficiency



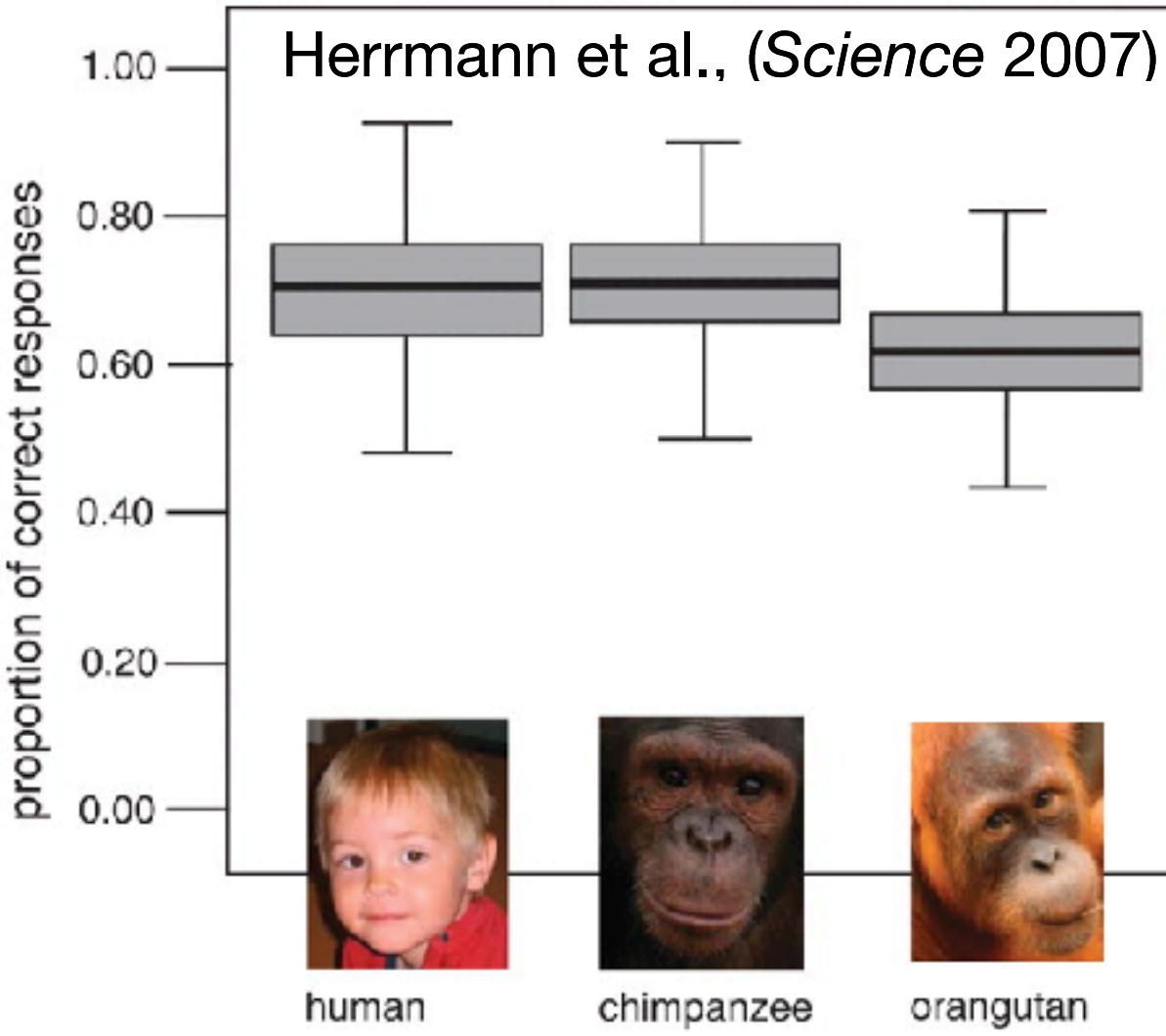


Next week: Social learning

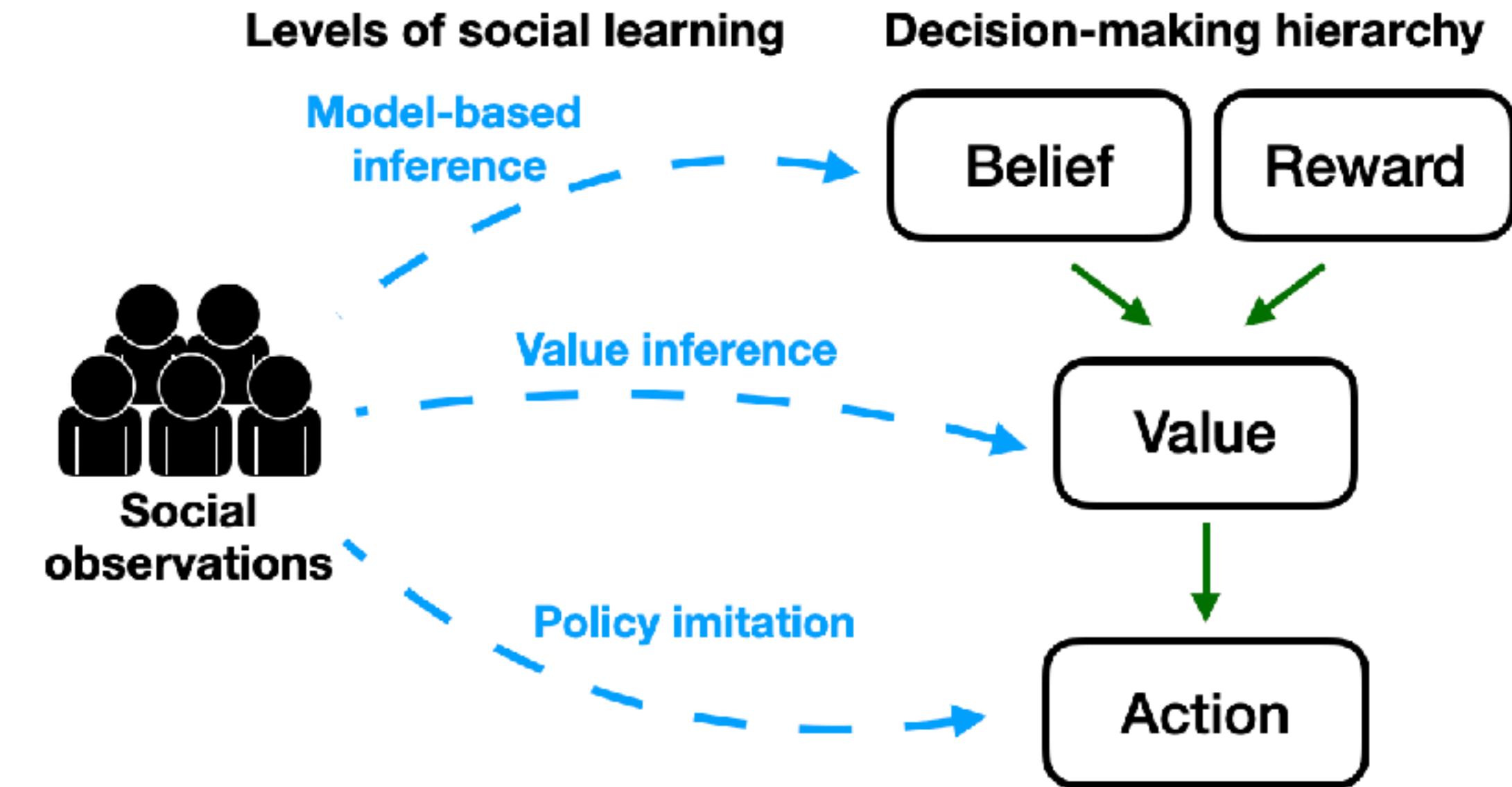
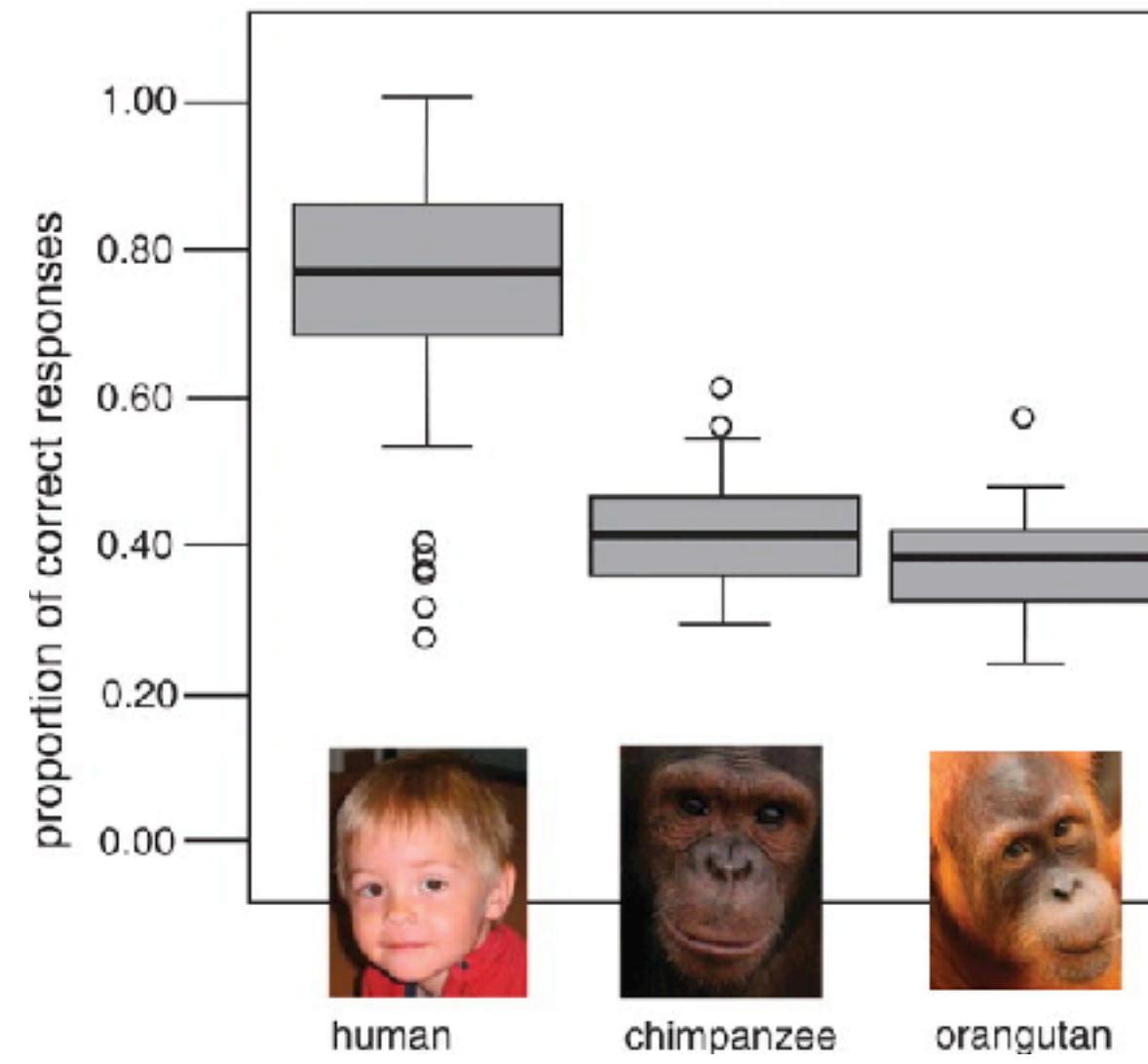
Alexandra Witt



Physical



Social



Witt et al., (PNAS 2024)