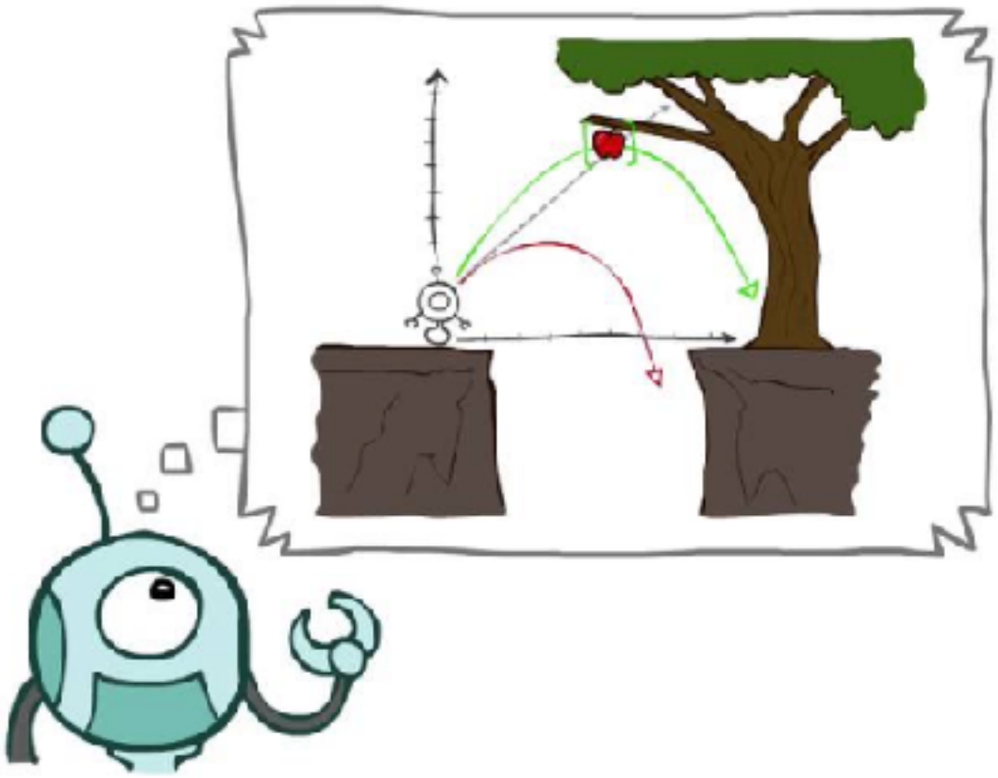
Learning rollout policy for internal planning in deep reinforcement learning agent

Metody planowania w głębokim uczeniu ze wzmocnieniem

Piotr Januszewski

Motivation

Humans make plans

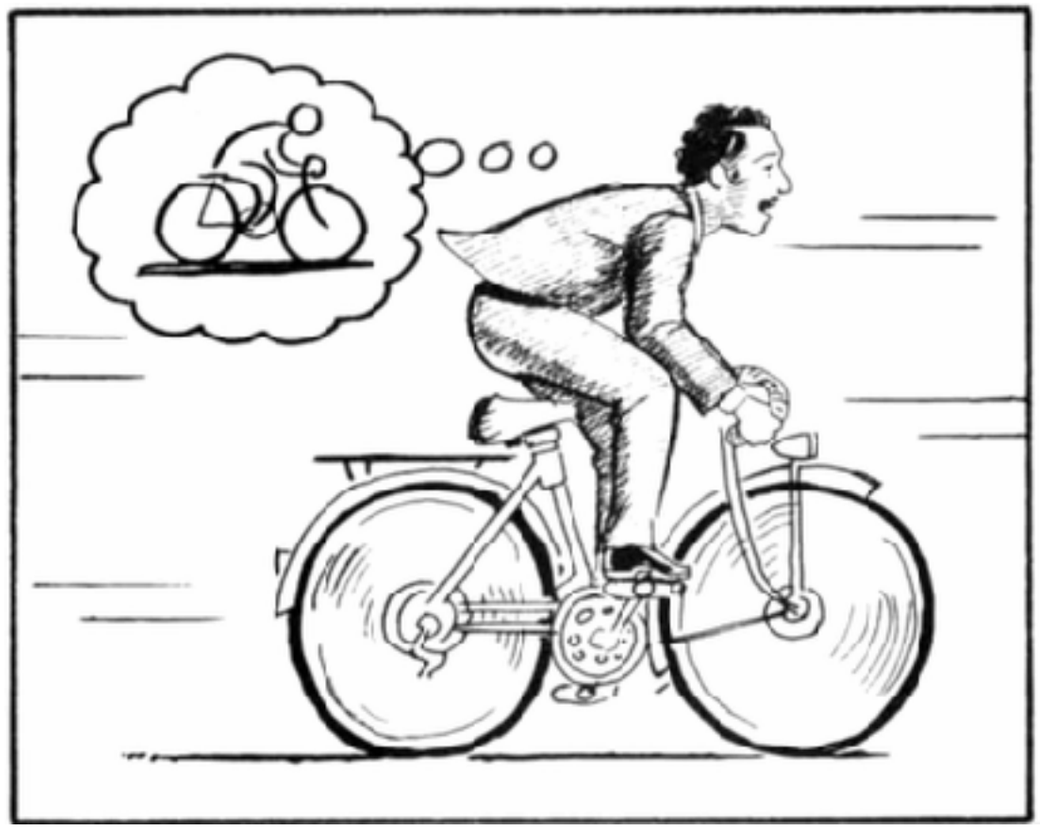


Source: http://ai.berkeley.edu/

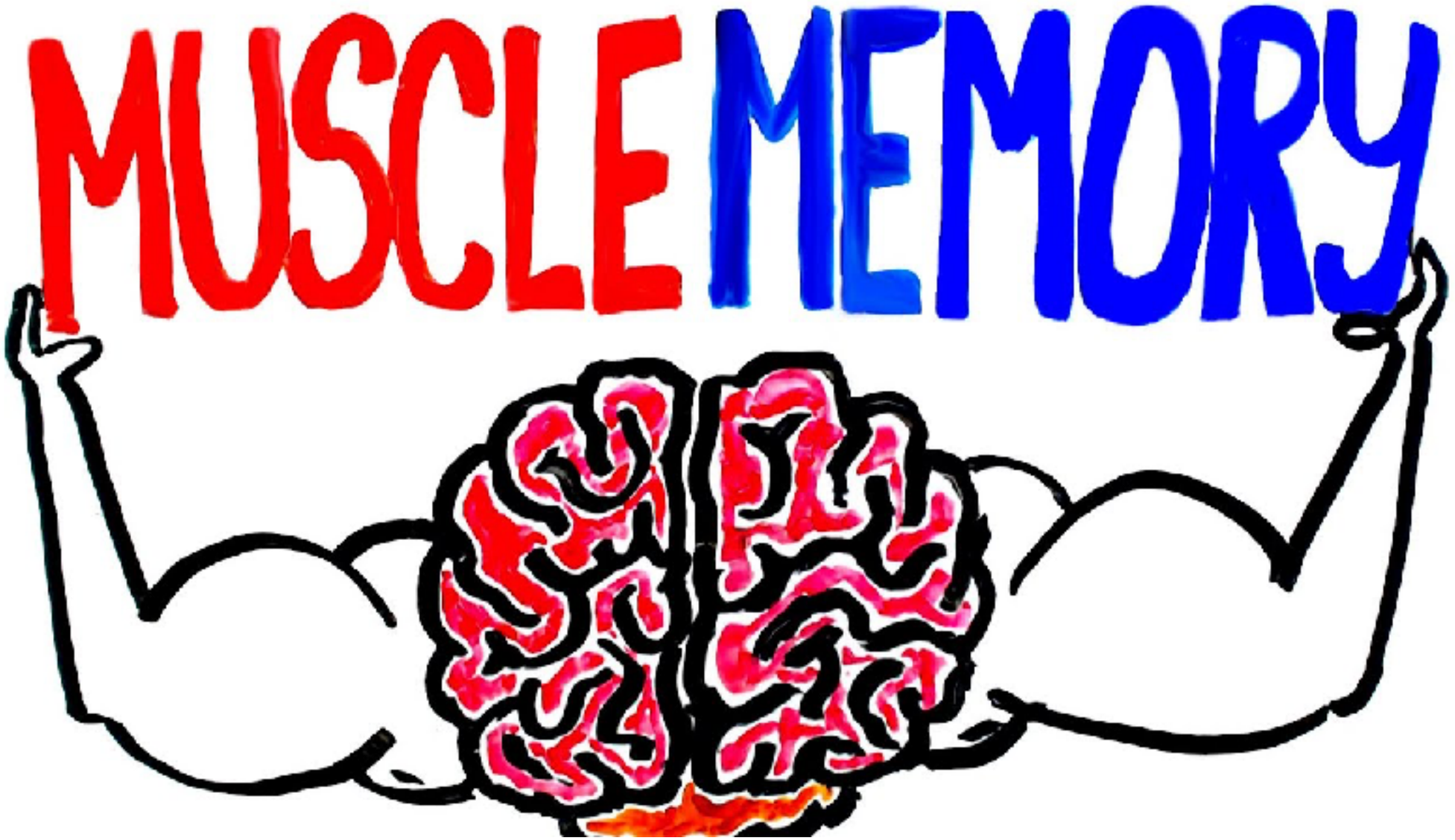
Mental model

The image of the world around us, which we carry in our head, is just a model. Nobody in his head imagines all the world, government or country. He has only selected concepts, and relationships between them, and uses those to represent the real system

~ Jay Wright Forrester, 1971



A World Model, from Scott McCloud's Understanding Comics.



Problem

Goal

The goal is to improve data efficiency without loss in performance compared to model-free methods. This work focuses on three benchmarks: an arcade game with dense rewards Boxing, a challenging environment with sparse rewards Freeway and a complex puzzle game Sokoban.

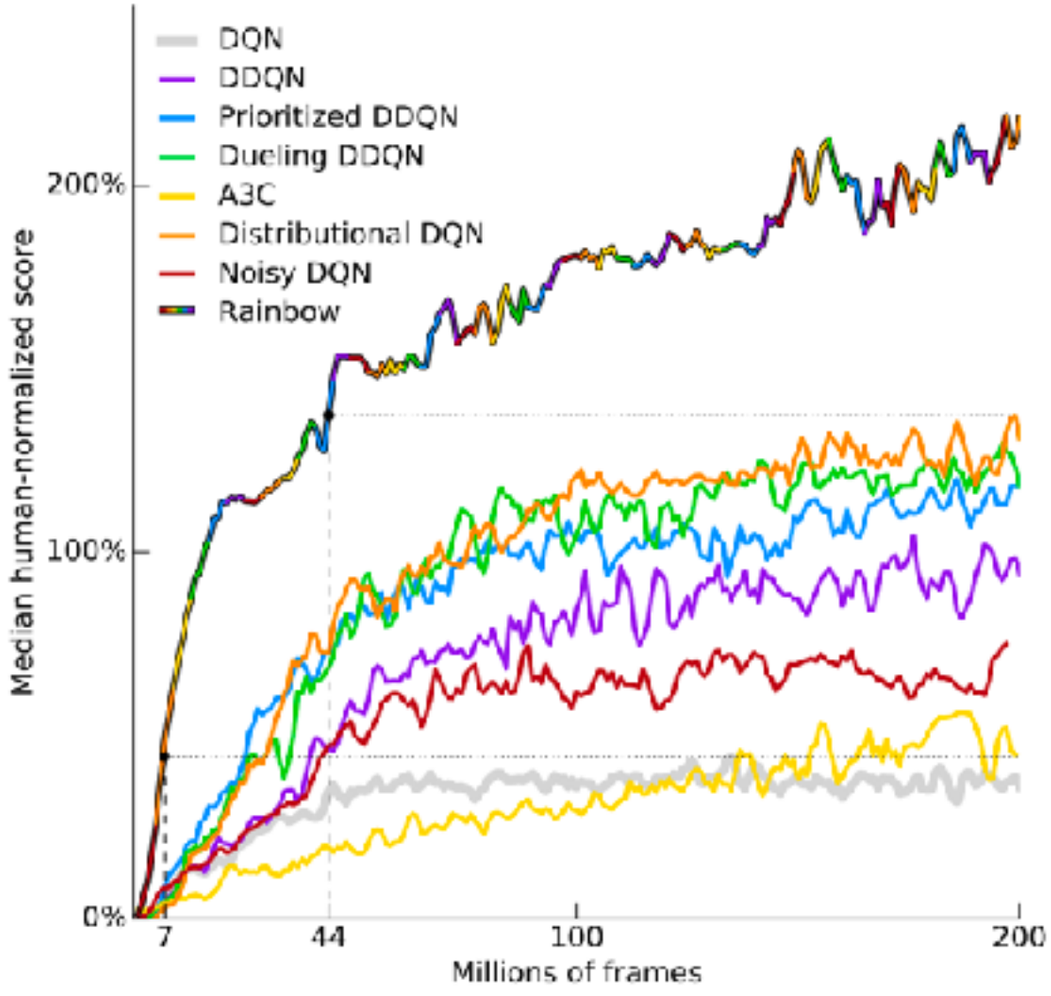
State of the art

State of the art

Model-free:

- Rainbow - a compilation of several independent improvements to the DQN algorithm made by the deep reinforcement learning community.

- PPO - the new family of policy gradient methods for reinforcement learning, which alternate between sampling data through interaction with the environment, and optimising a surrogate objective function using stochastic gradient ascent.



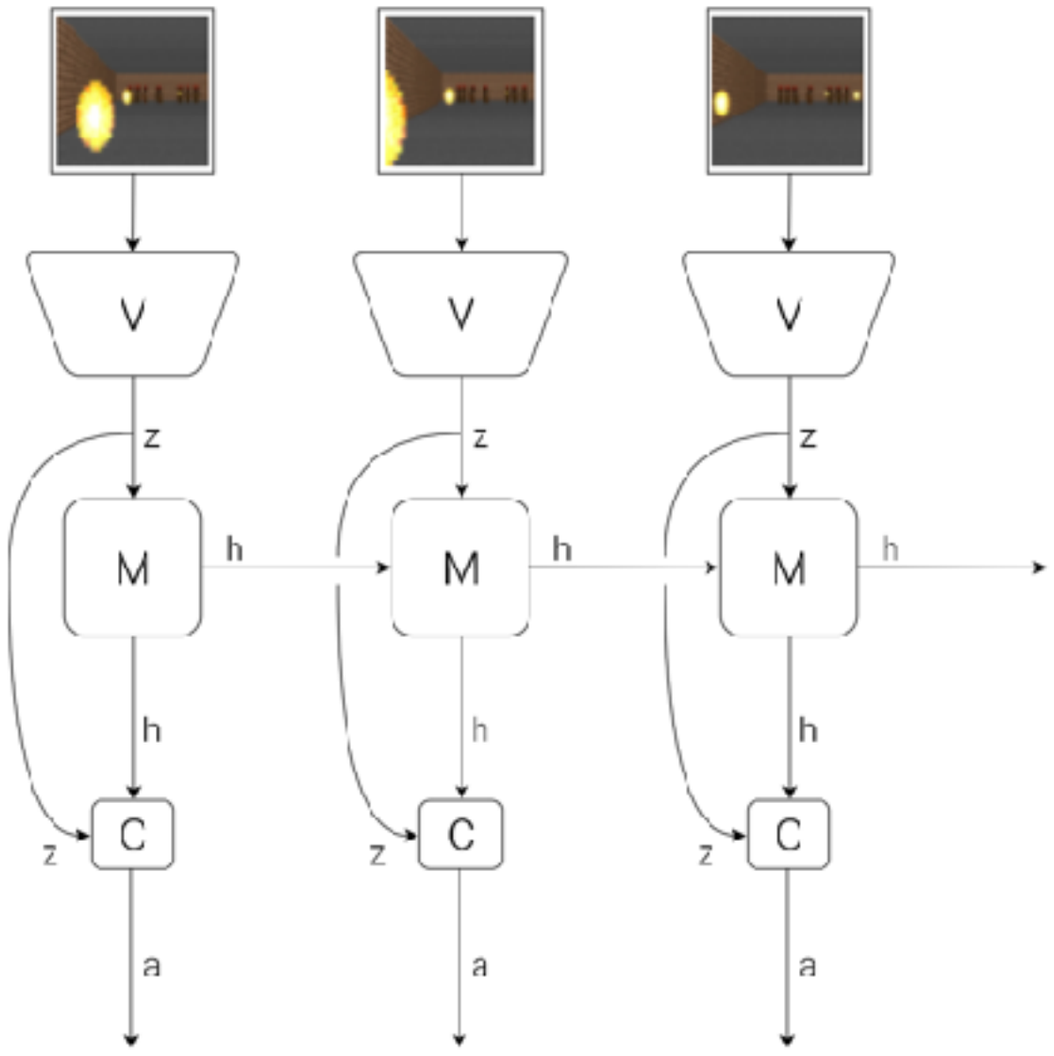
Median human-normalised performance across 57 Atari games from the Rainbow paper.

State of the art

Model-based	World model	Planning strategy
SimPLe (Kaiser et al., 2019)	Observation-level model	Model used to generate more experience
World Models (Ha & Schmidhuber, 2018)	Abstract-level model	Model used to generate more experience
PlaNet (Hafner et al., 2019)	**Abstract-level model**	**Model used to search for the best next action**

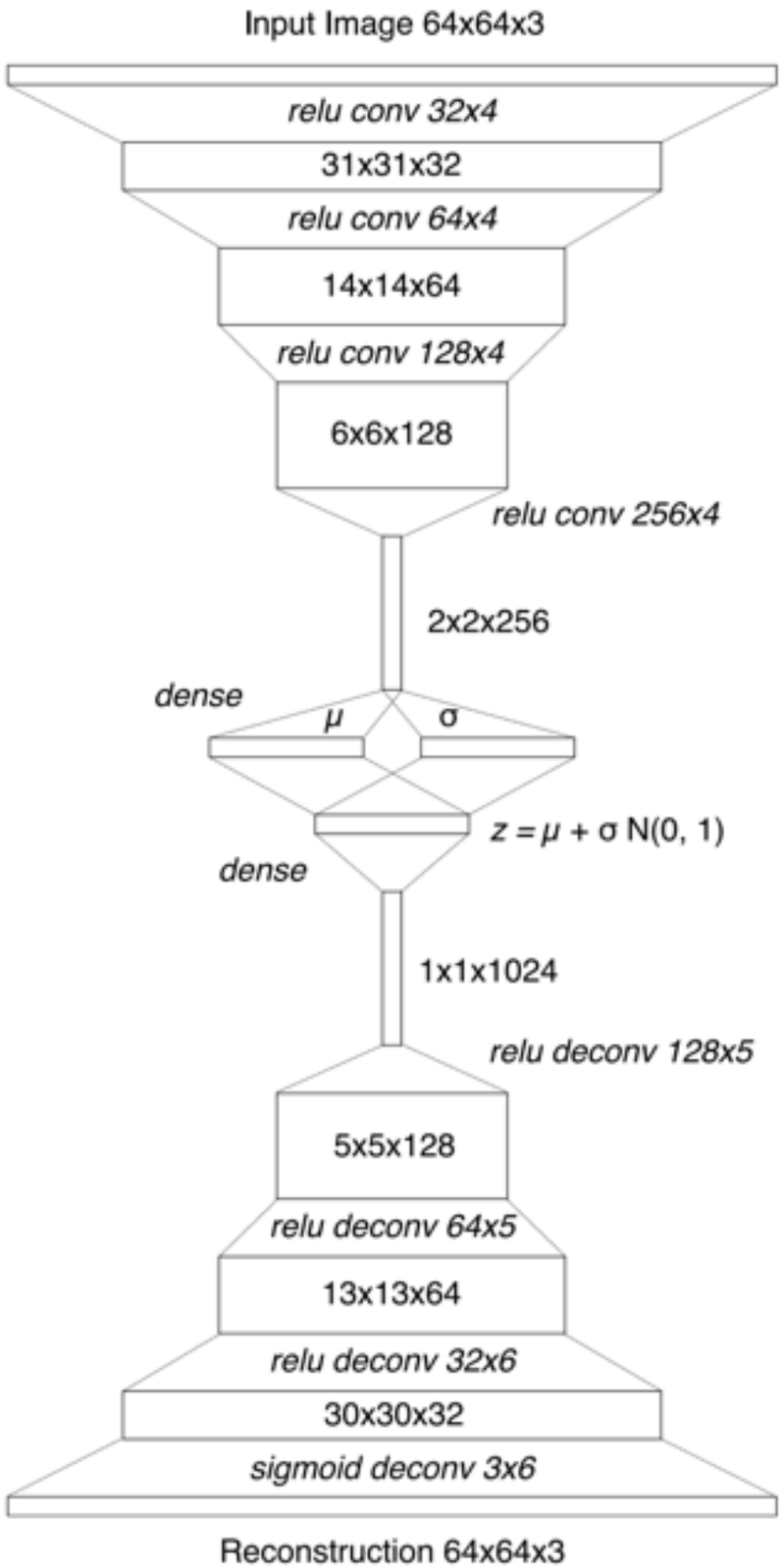
Solutions description and experiments

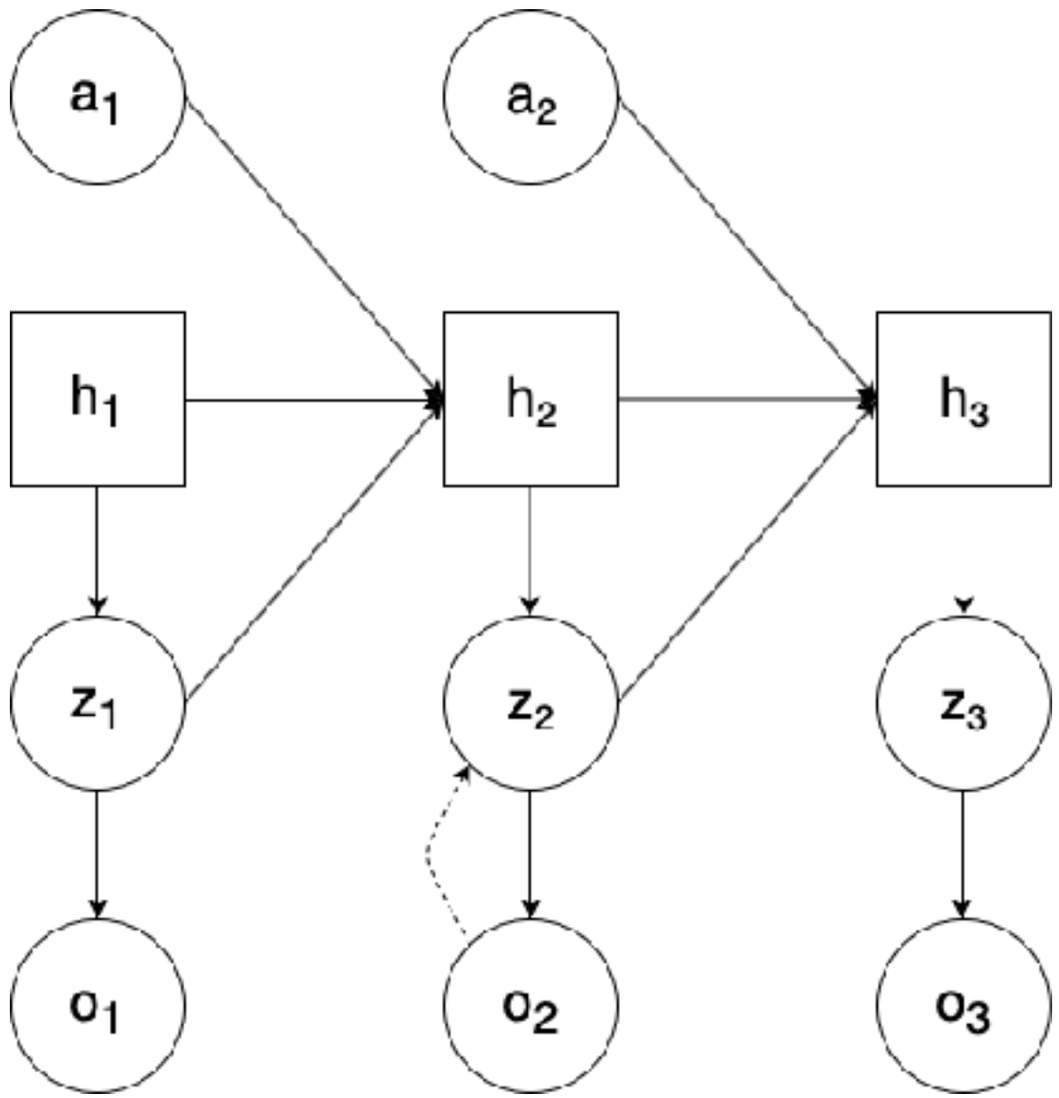
Original World Models (OWM)



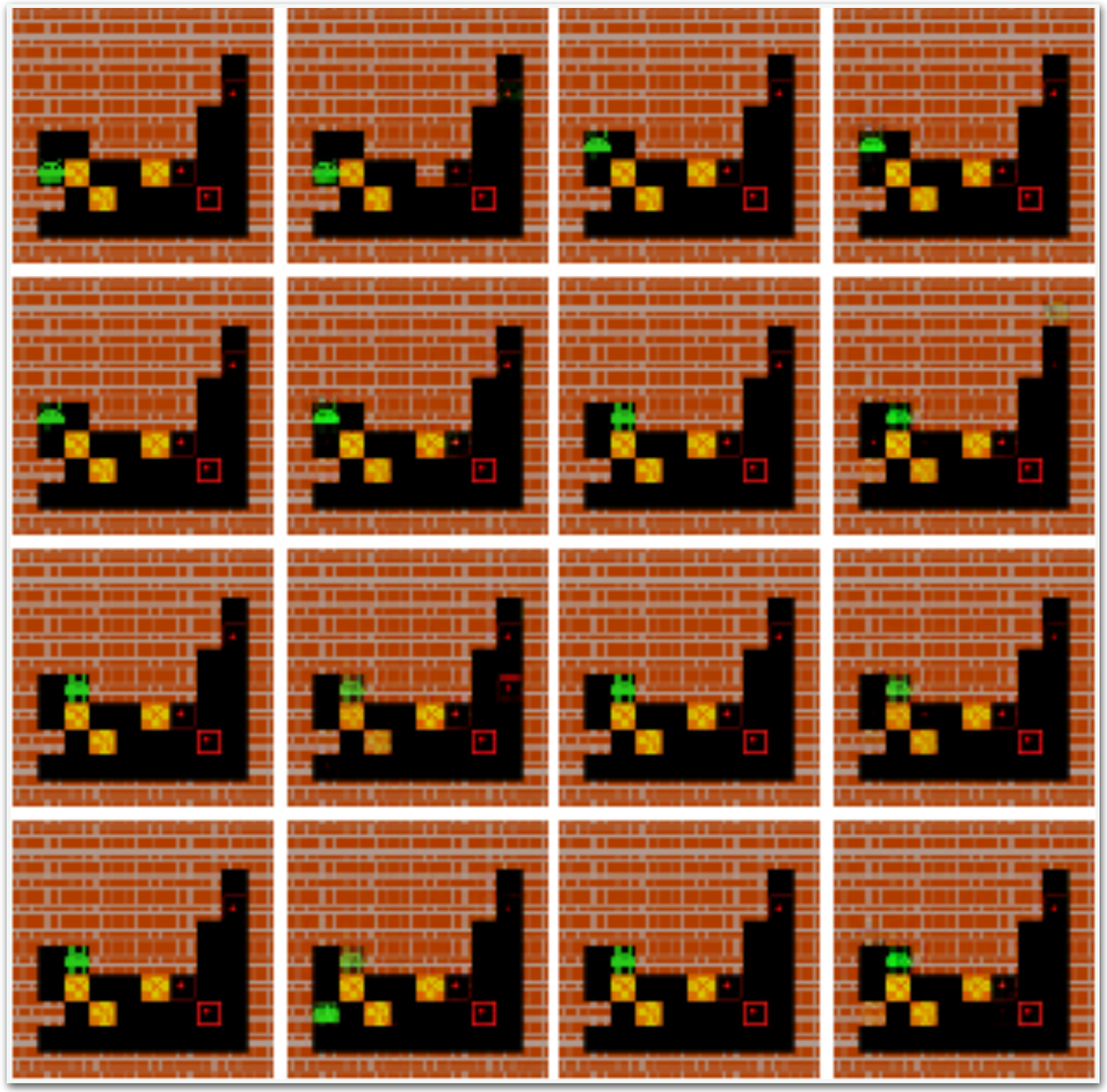
World Models agent consists of three components that work closely together: **V**ision, **M**emory, and **C**ontroller

Vision


Input Image 64x64x3
relu conv 32x4
31x31x32
relu conv 64x4
14x14x64
relu conv 128x4
6x6x128
relu conv 256x4
2x2x256
dense
μ
σ
z = μ + σ N(0, 1)
dense
1x1x1024
relu deconv 128x5
5x5x128
relu deconv 64x5
13x13x64
relu deconv 32x6
30x30x32
sigmoid deconv 3x6
Reconstruction 64x64x3

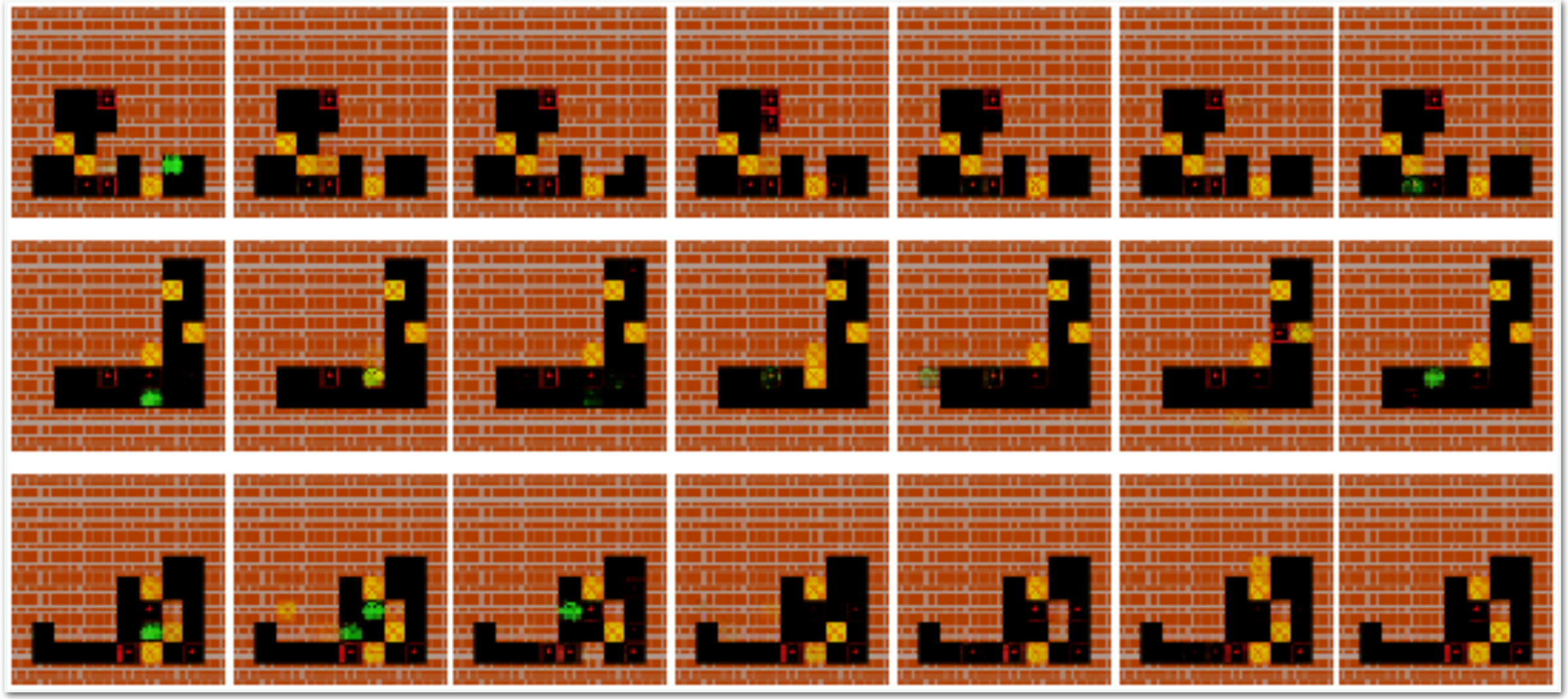


Memory



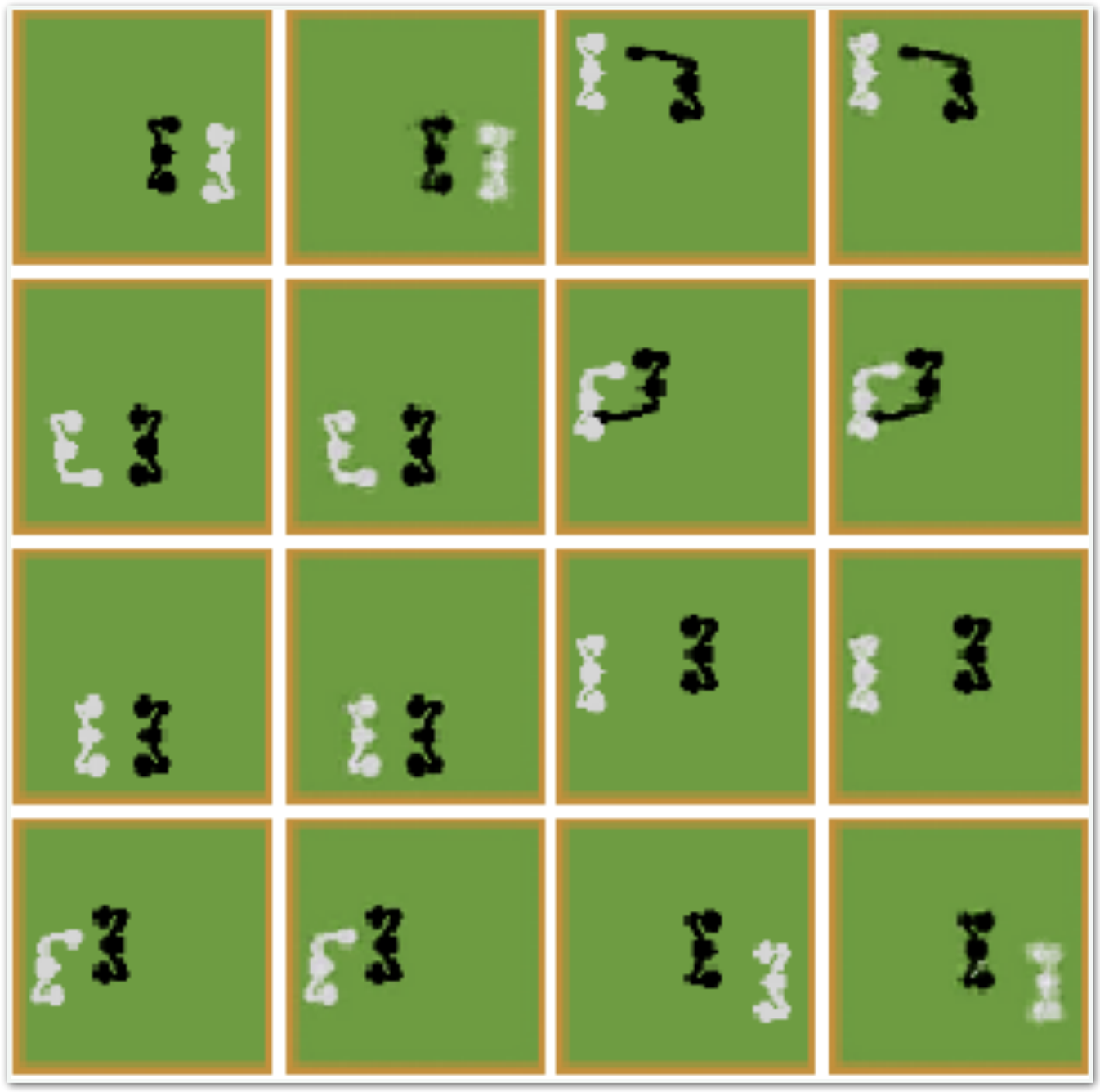
Vision

OWM for Sokoban



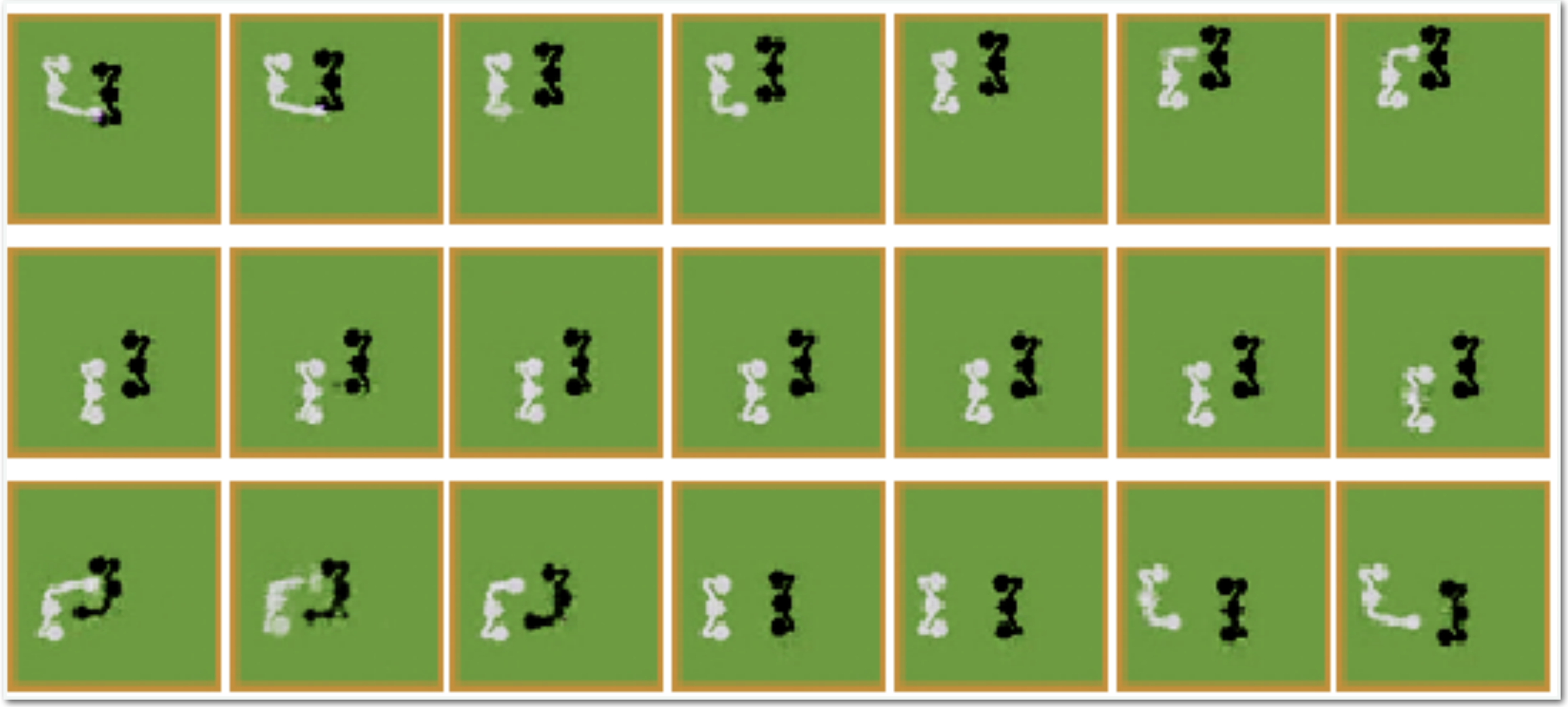
Memory

OWM for Sokoban



Vision

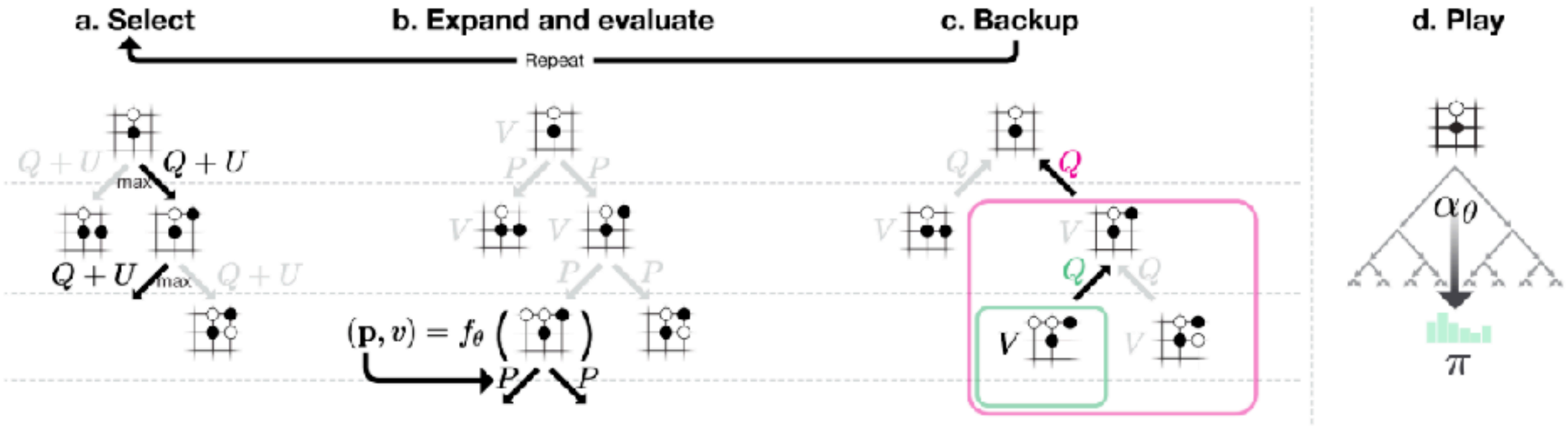
OWM for Boxing



Memory

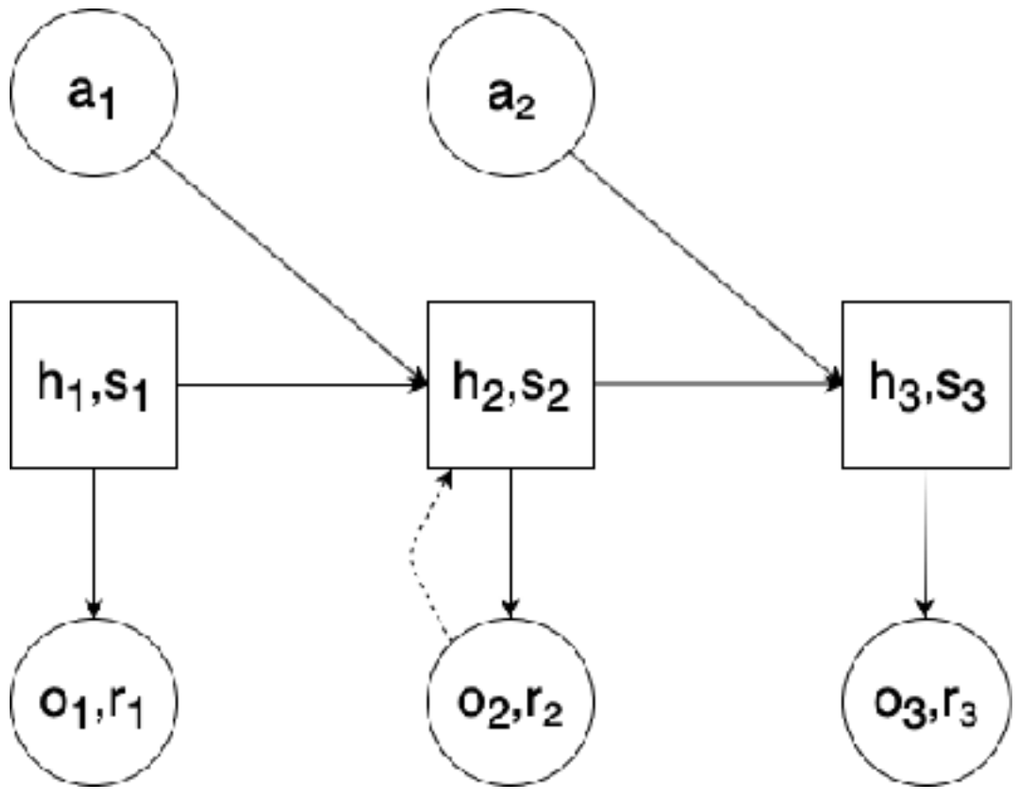
OWM for Boxing

World Models and AlphaZero (W+A)

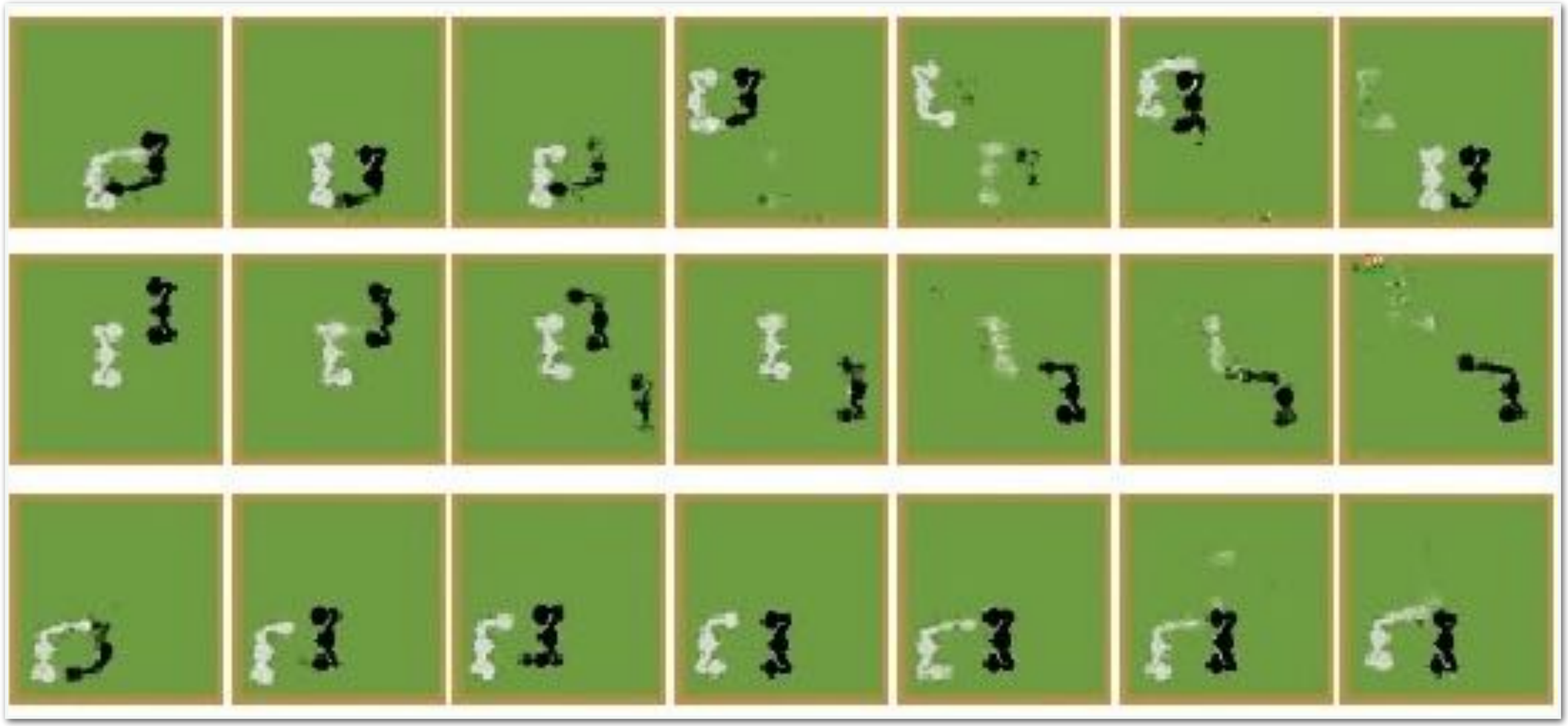


Controller

AlphaZero tree search algorithm



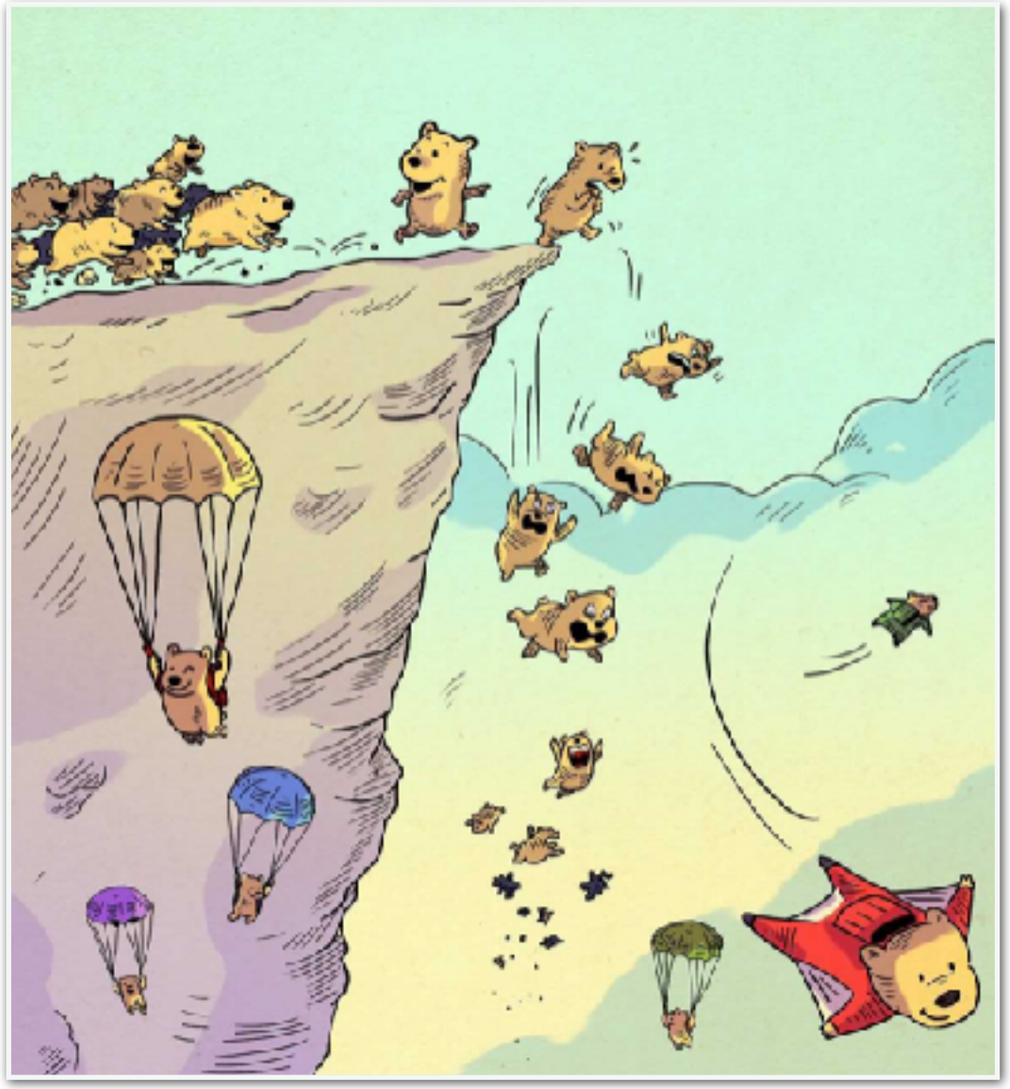
Memory



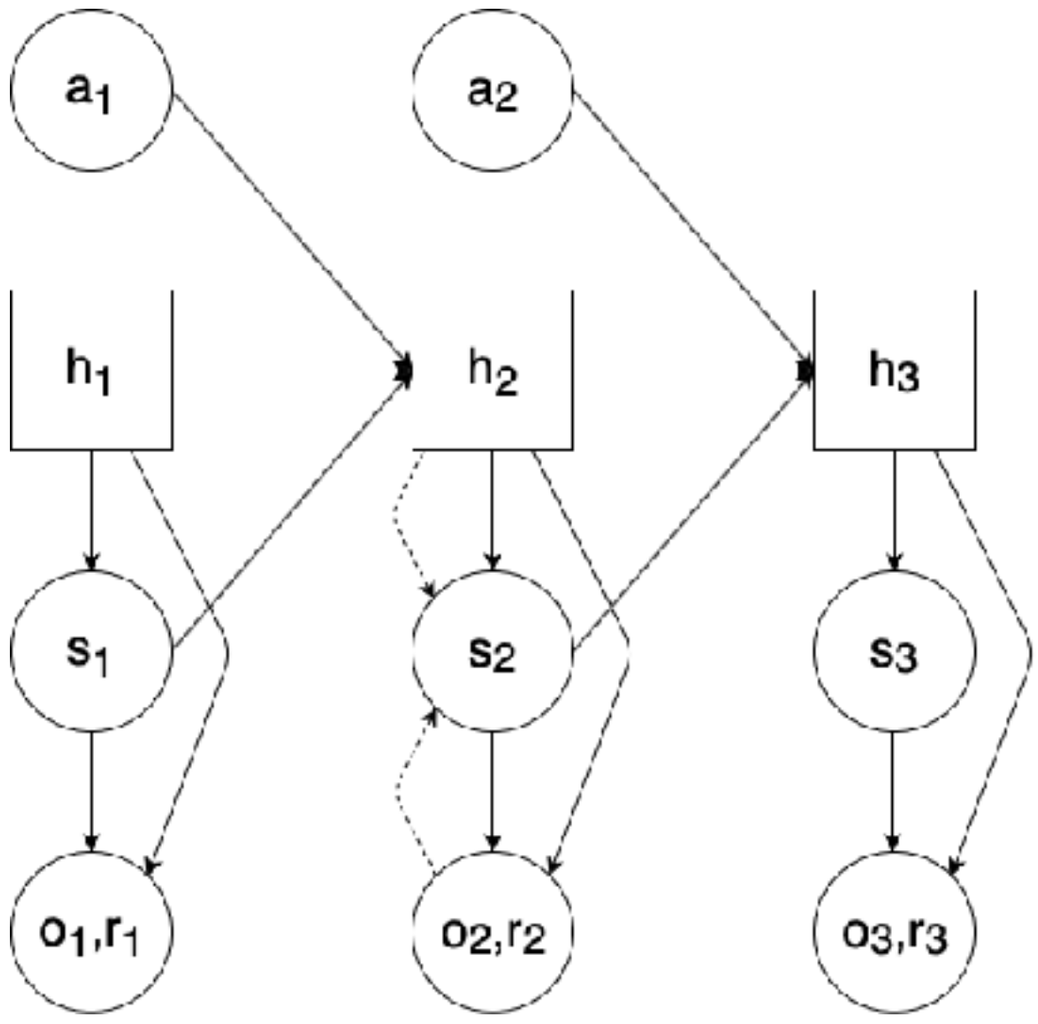
Memory

W+A for Boxing

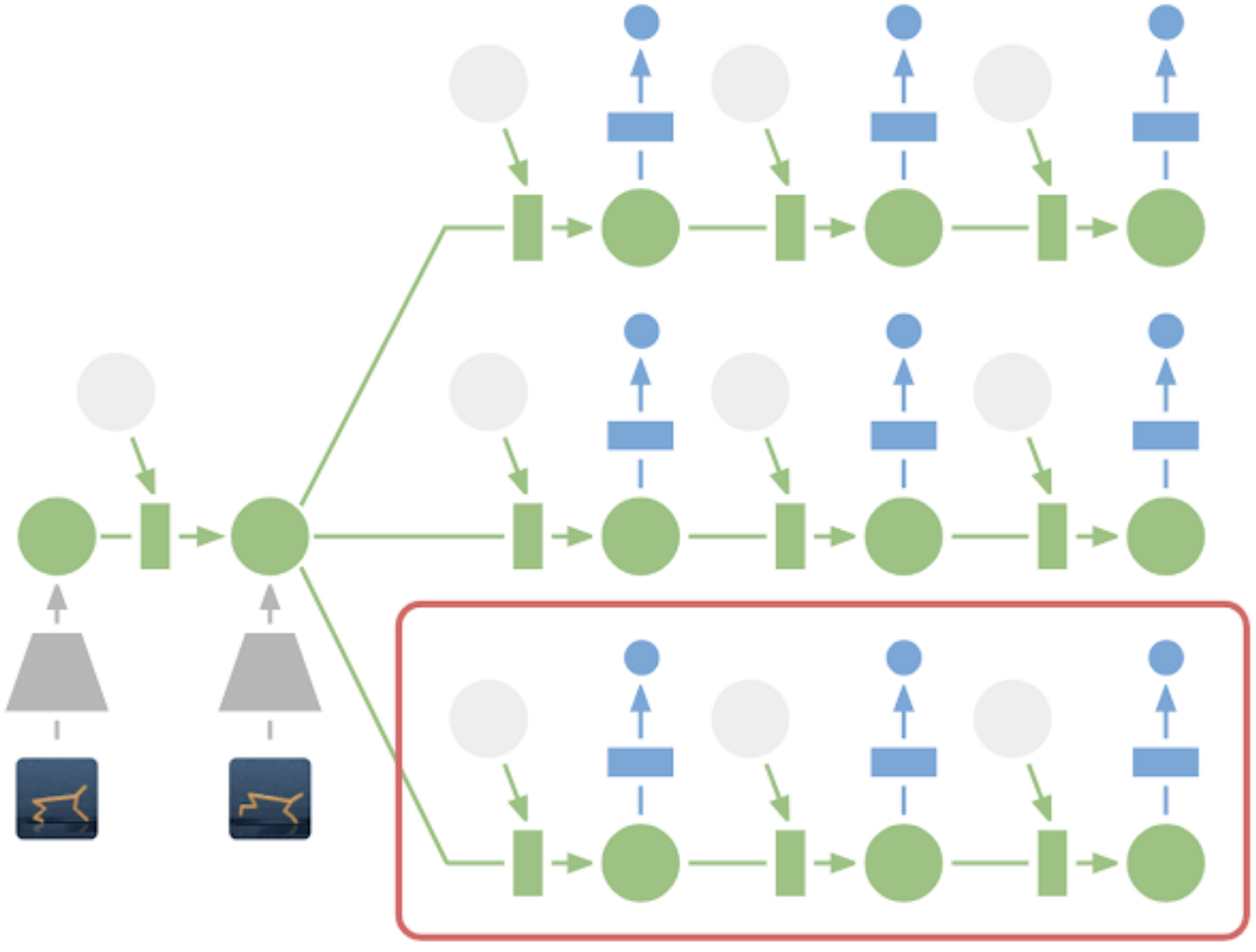
Discrete PlaNet (DPN)



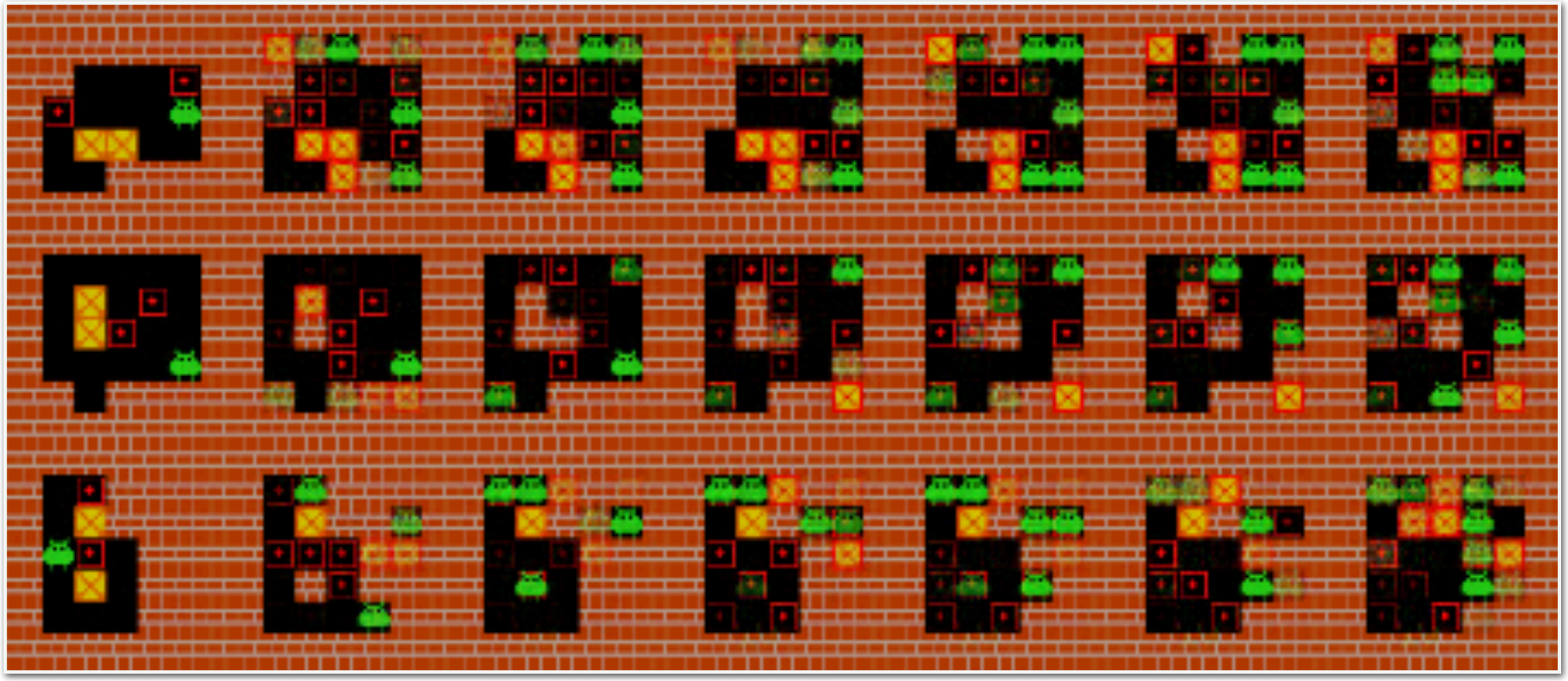
Survival of the fittest.



Memory

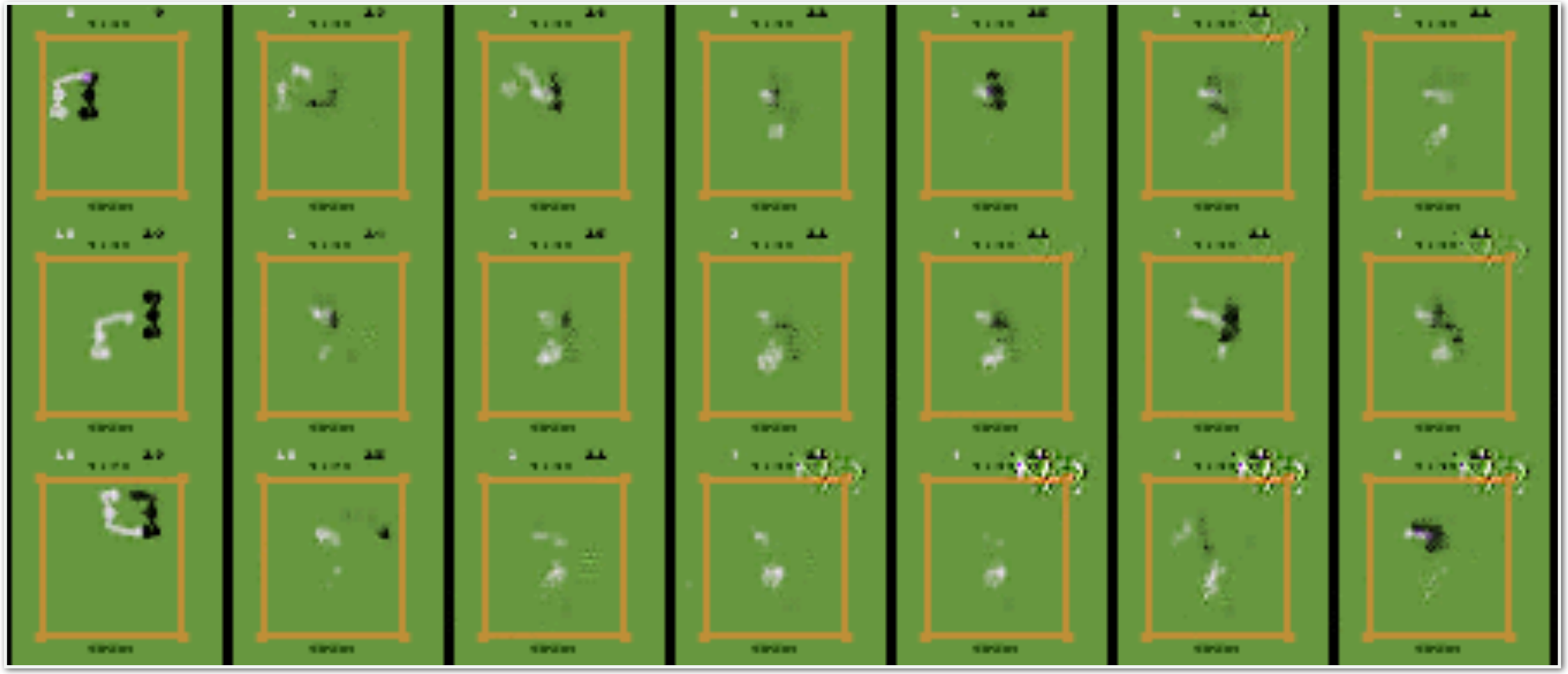


Planner



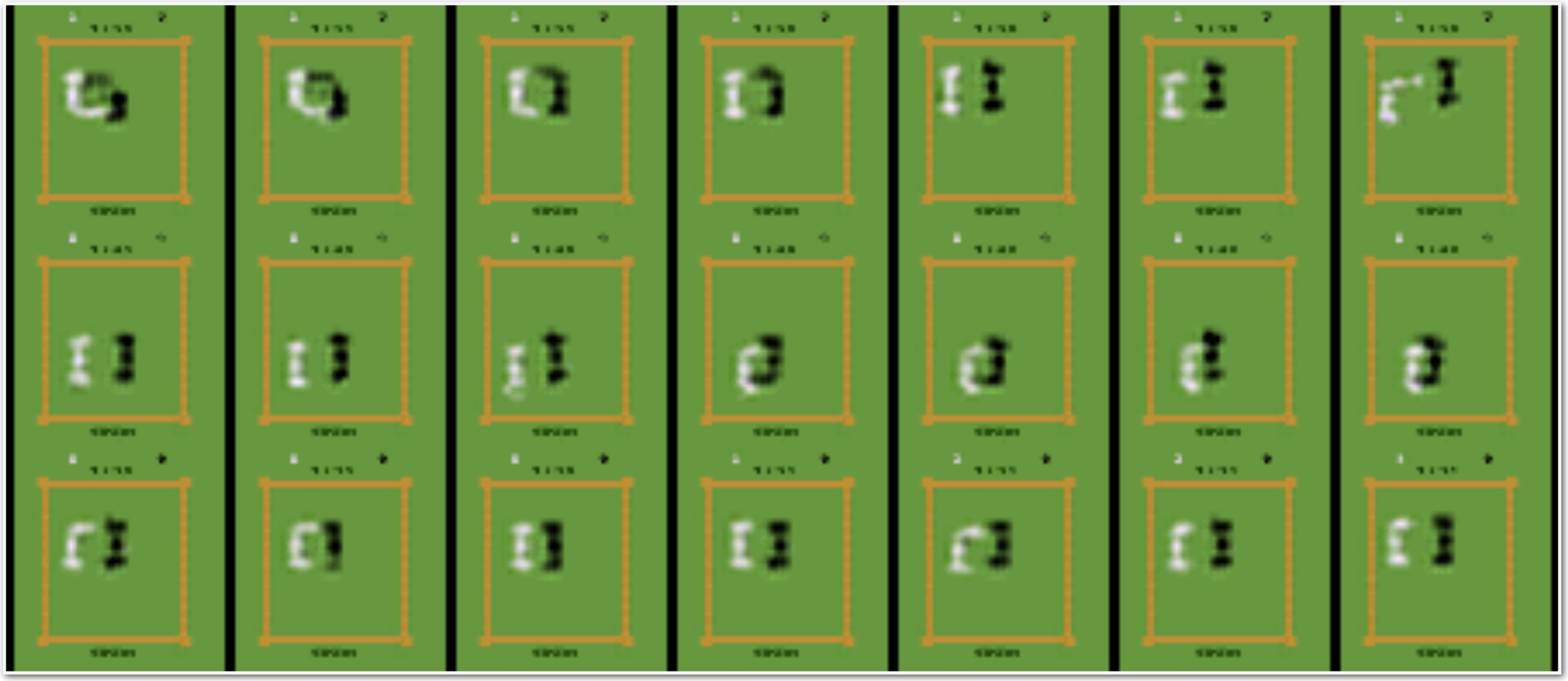
World model

DPN for Sokoban



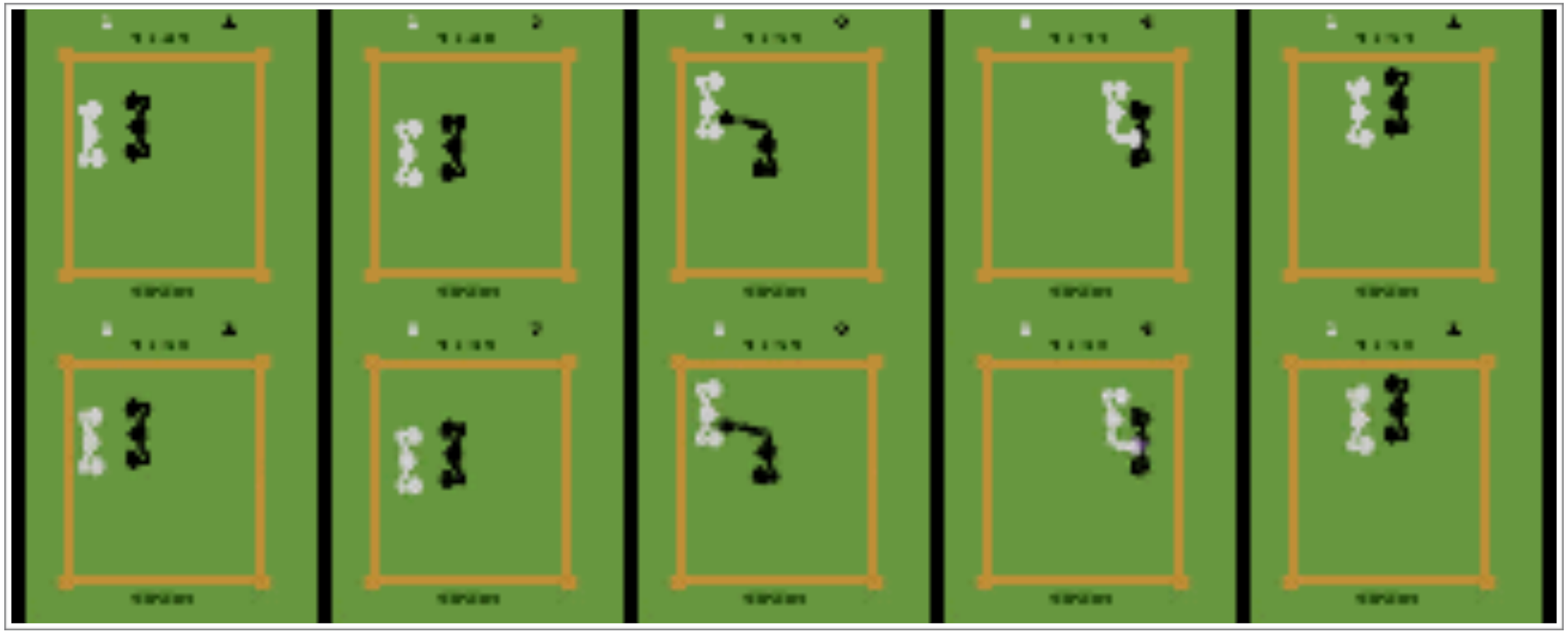
World model

DPN for Boxing



World model

Tuned DPN for Boxing



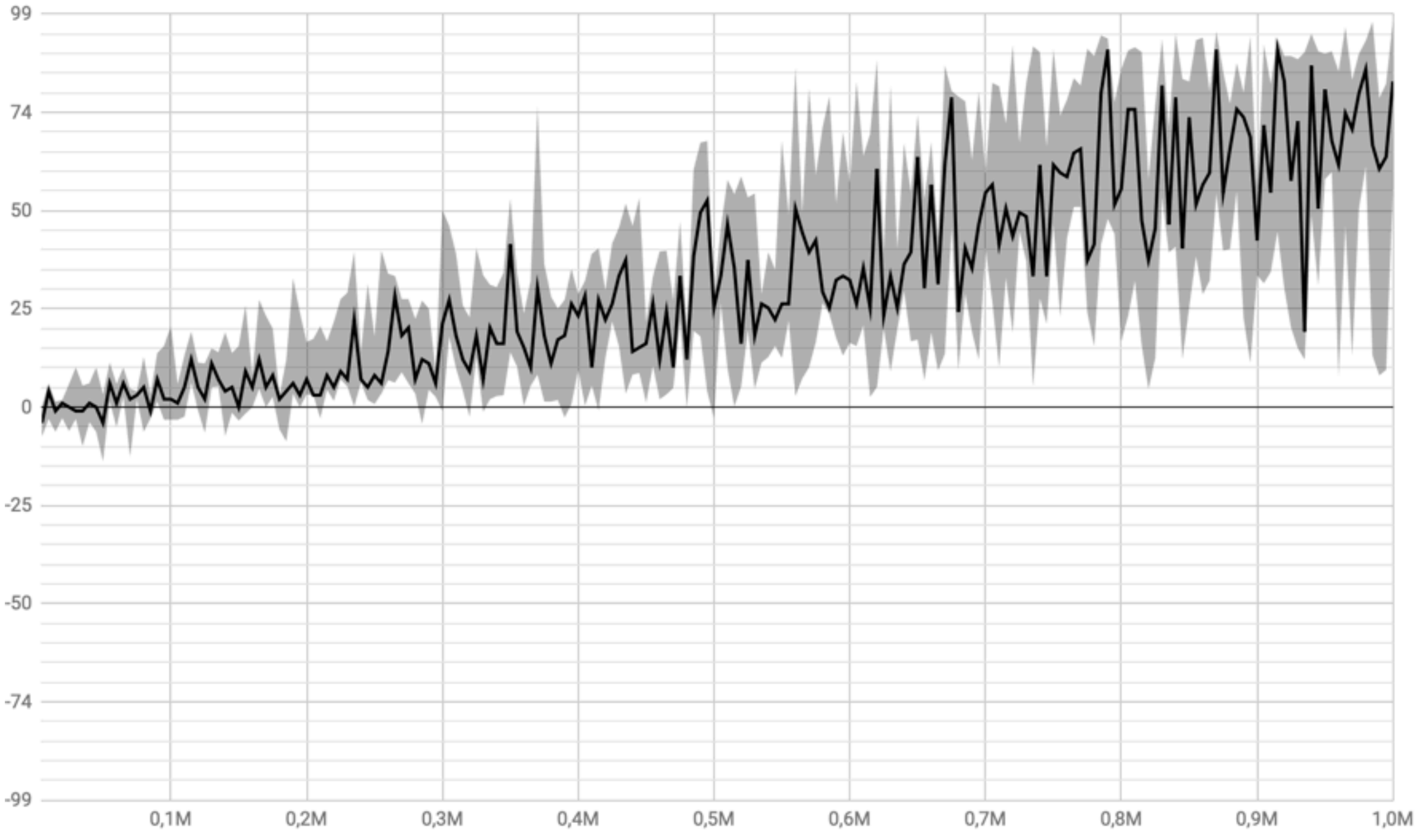
World model

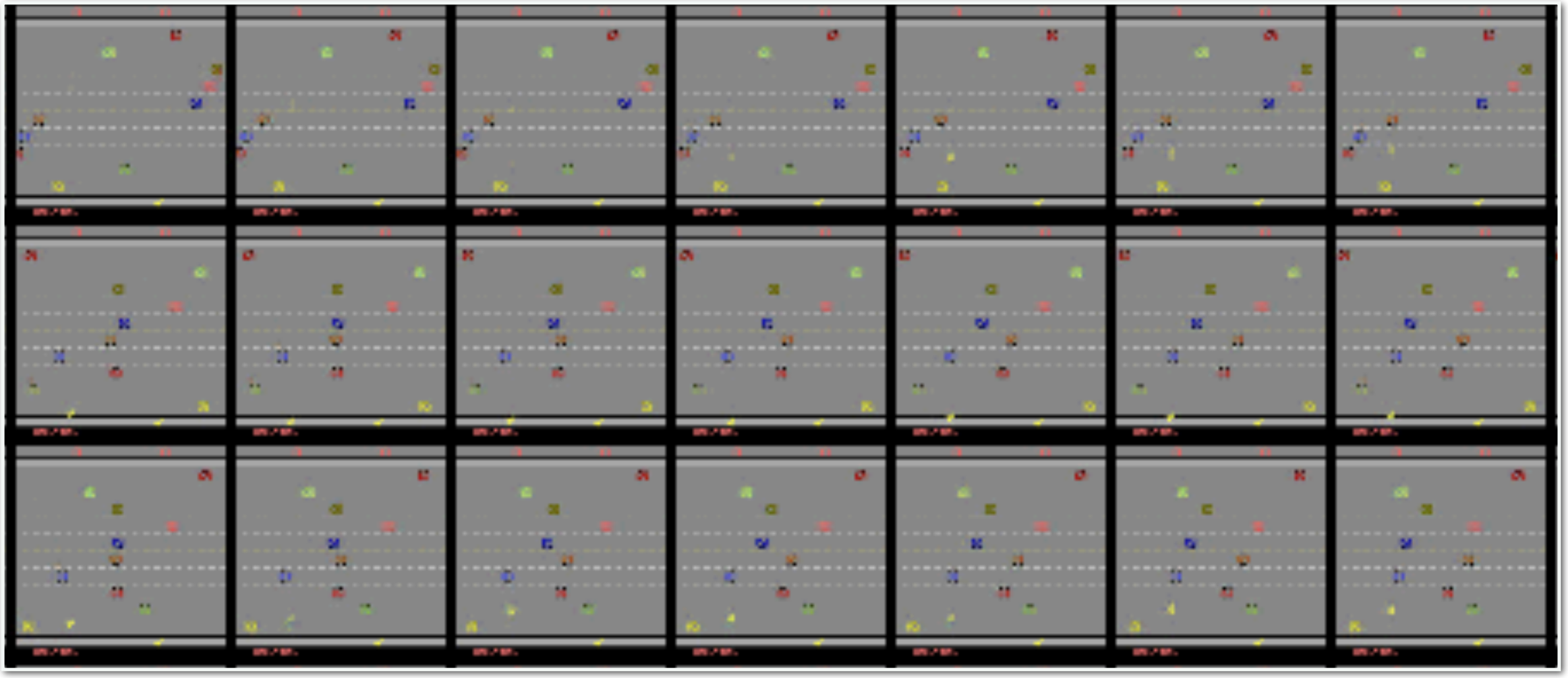
Tuned DPN for Boxing

Planner

Tuned DPN for Boxing

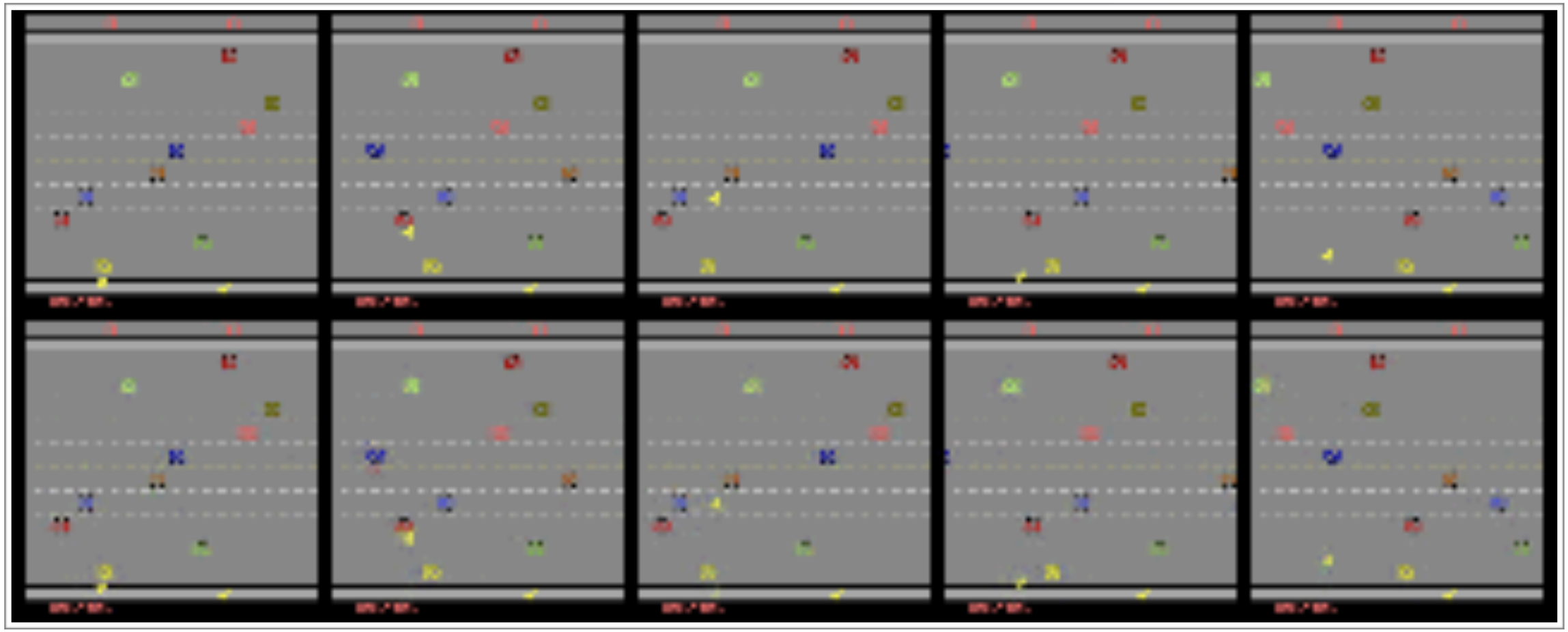
DPN for Boxing





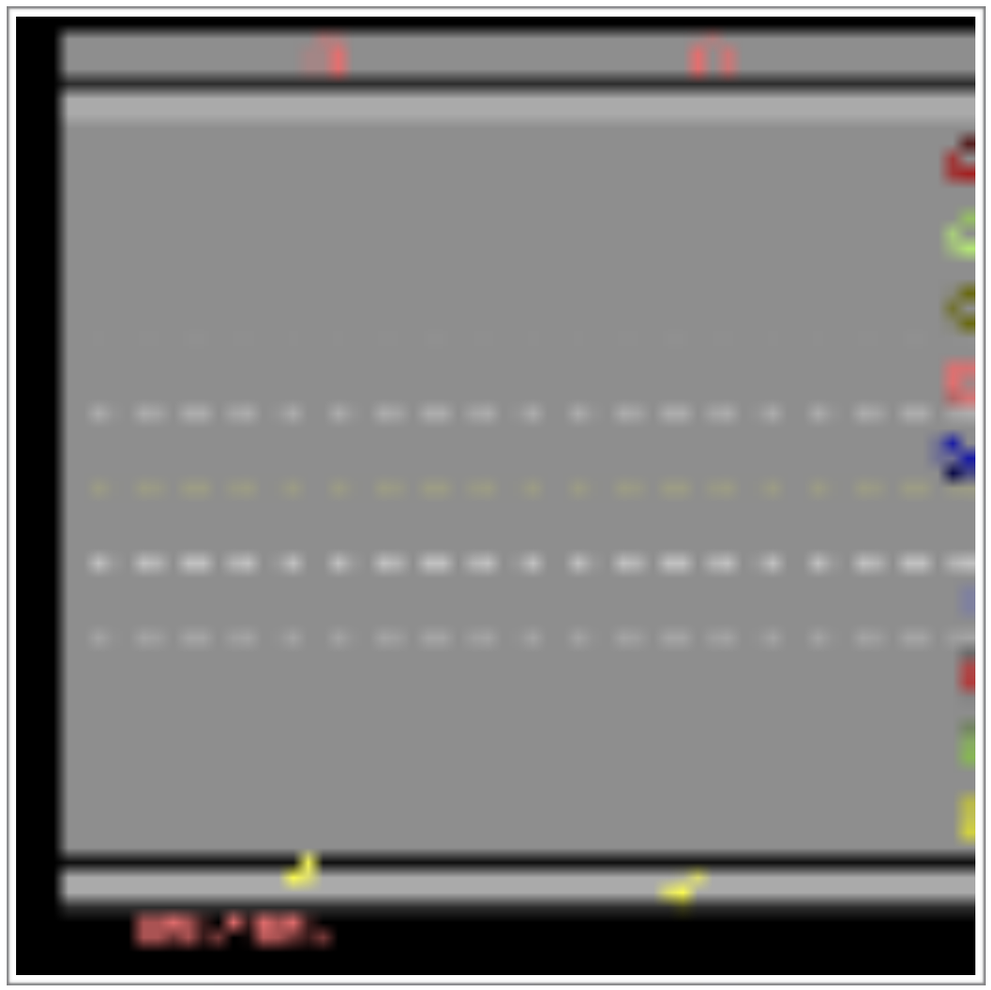
World model

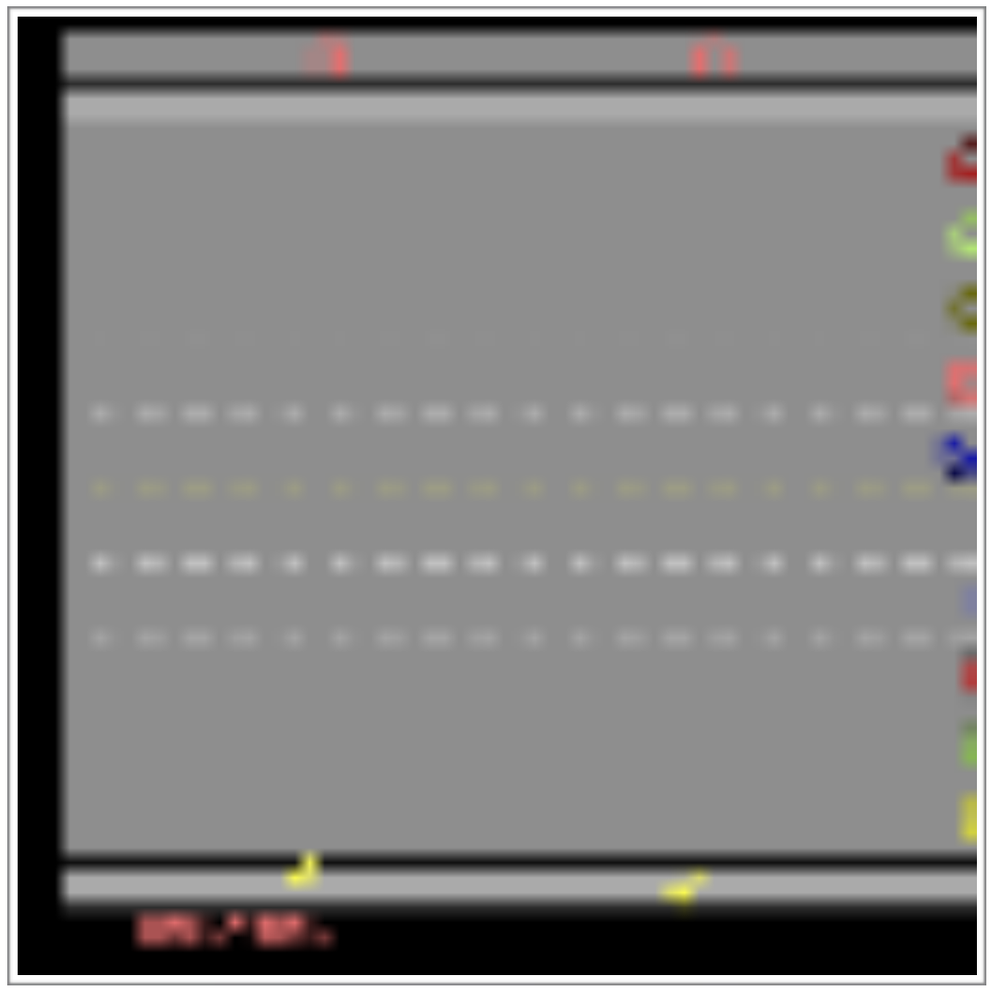
DPN for Freeway



World model

DPN for Freeway

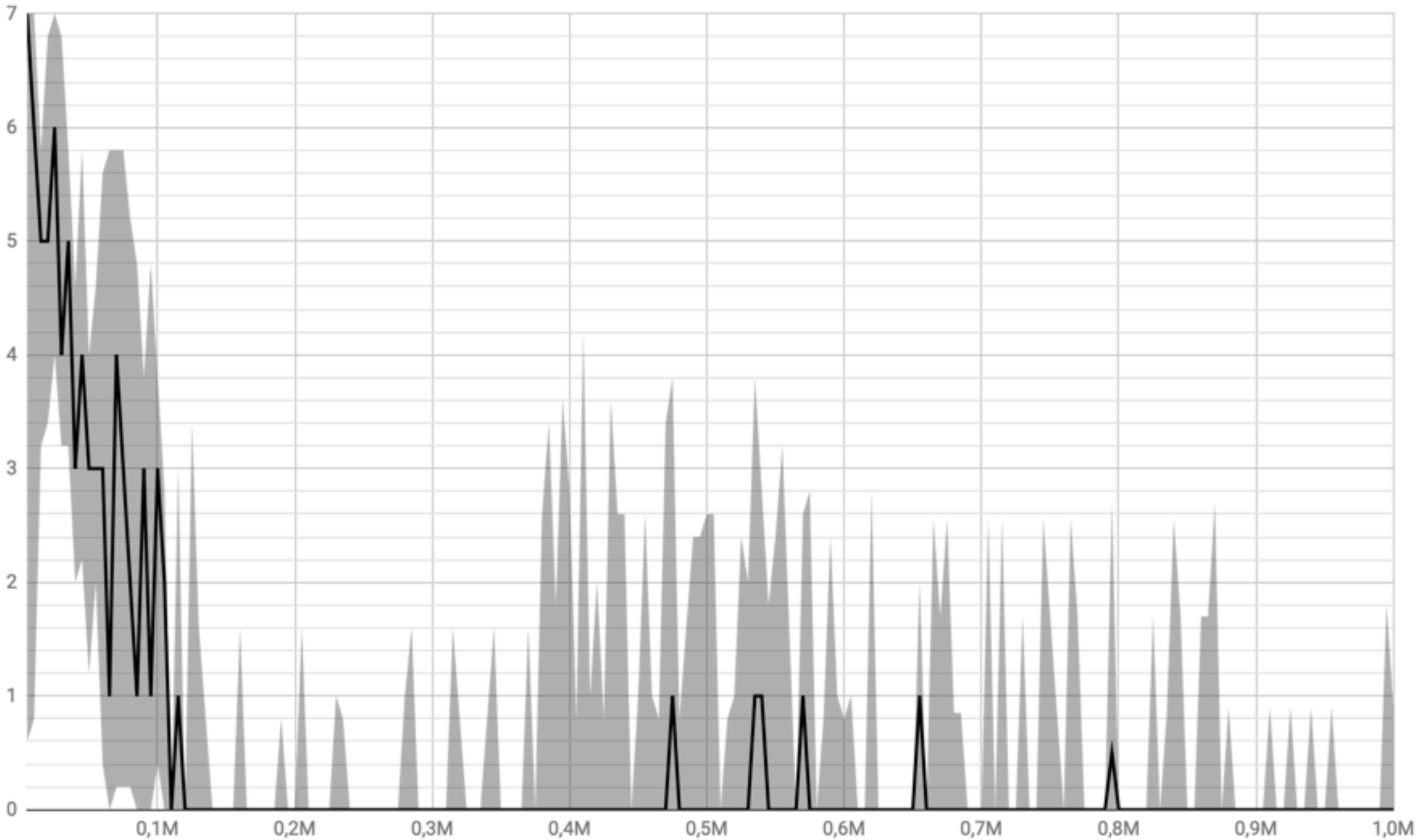




Planner

DPN for Freeway

DPN for Freeway



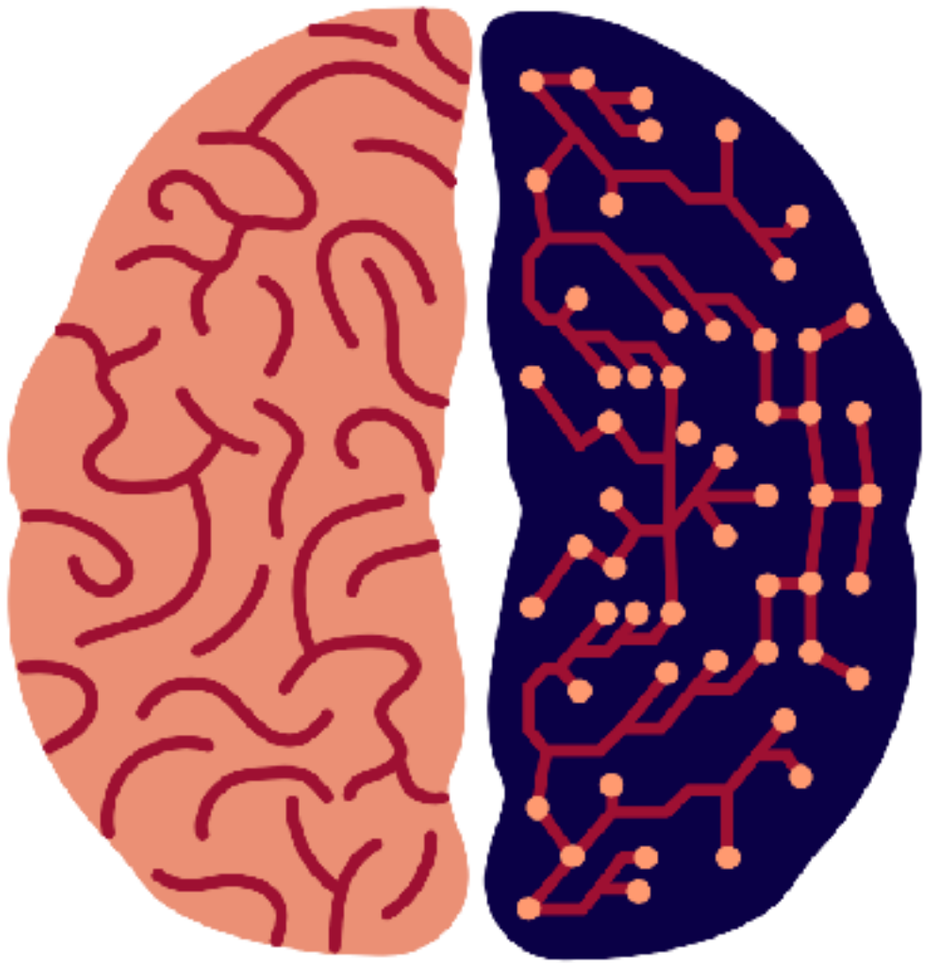
Final results for Boxing

Algorithm	100K	500K	1M
Ours	**6,2 (10,7)**	35,2 (8,3)	78,2 (19,1)
SimPLe	**9,1 (8,8)**	NDA	NDA
PPO	**-3,9 (6,4)**	3,5 (3,5)	19,6 (20,9)
Rainbow	**0,9 (1,7)**	58,2 (16,5)	80,3 (5,6)
Random	0.3		

Mean scores and standard deviations (in brackets) over five training runs of DPN in Boxing.

Conclusions and future work

Conclusions



Source: https://course.elementsofai.com/

Future work

- Future work could focus on extending this method to other challenging tasks like: sparse rewards environments, i.e. Freeway, and complex puzzle games with massive state-space sizes, i.e. Sokoban.

- DPN, unlike model-based baseline SimPLe, hold promise of increased performance with an increased computational budget for planning. This hypothesis could be put to the extensive test too.

- Furthermore, generalisation of the DPN world model to different tasks in the same or very similar environments could be explored.

Thank you for your attention

Questions?