



Reinforcement Learning: Past, Present, and Future Perspectives

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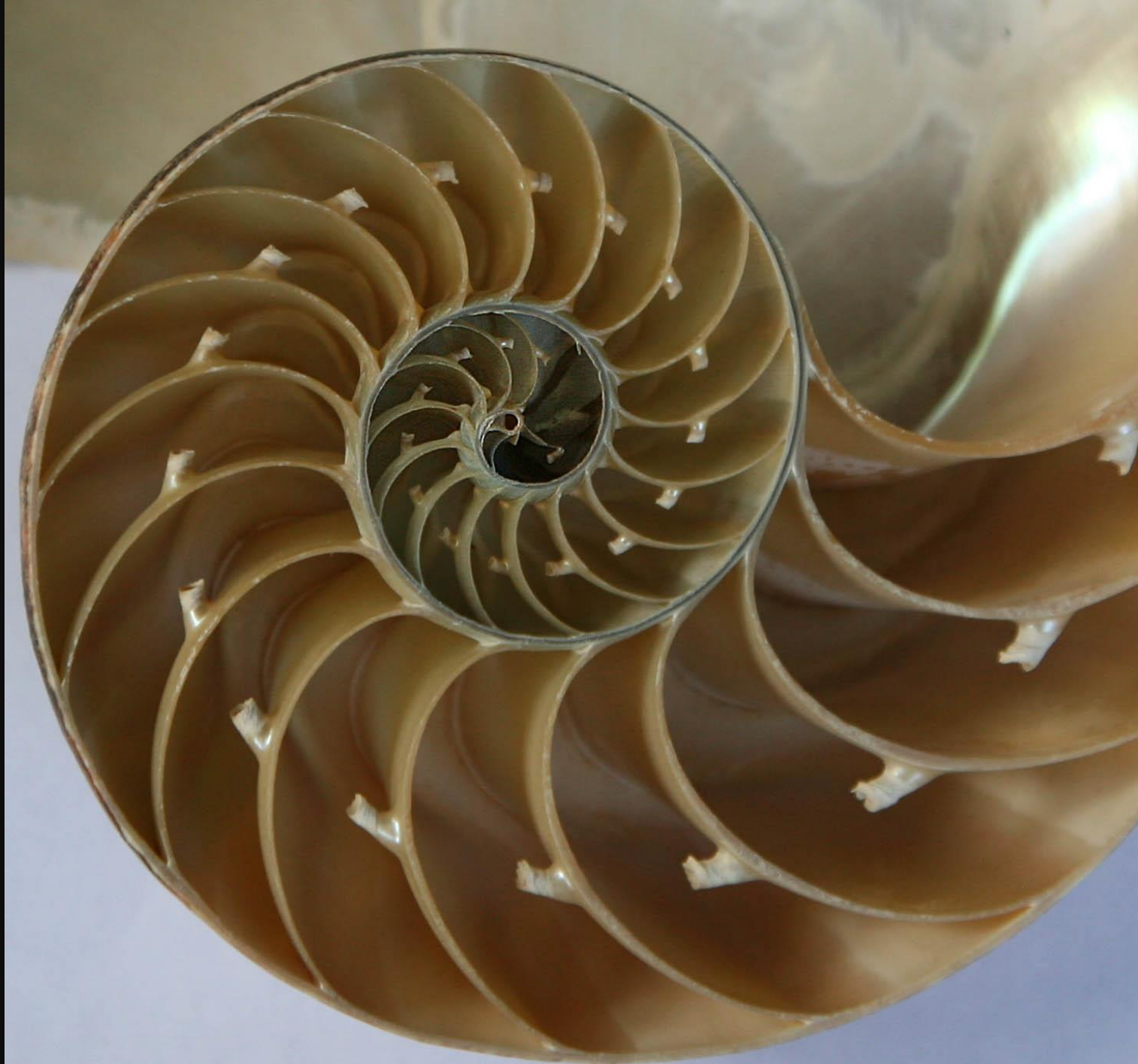


**Reinforcement Learning =
Decision Making and
Learning
under Uncertainty**



Plan for Today

1. Formalizing RL
2. Value Functions
3. Exploration
4. Policy Gradient and Actor Critic Approaches
5. Generalization
6. Structure
7. Models
8. New Challenges



1. Formalizing RL

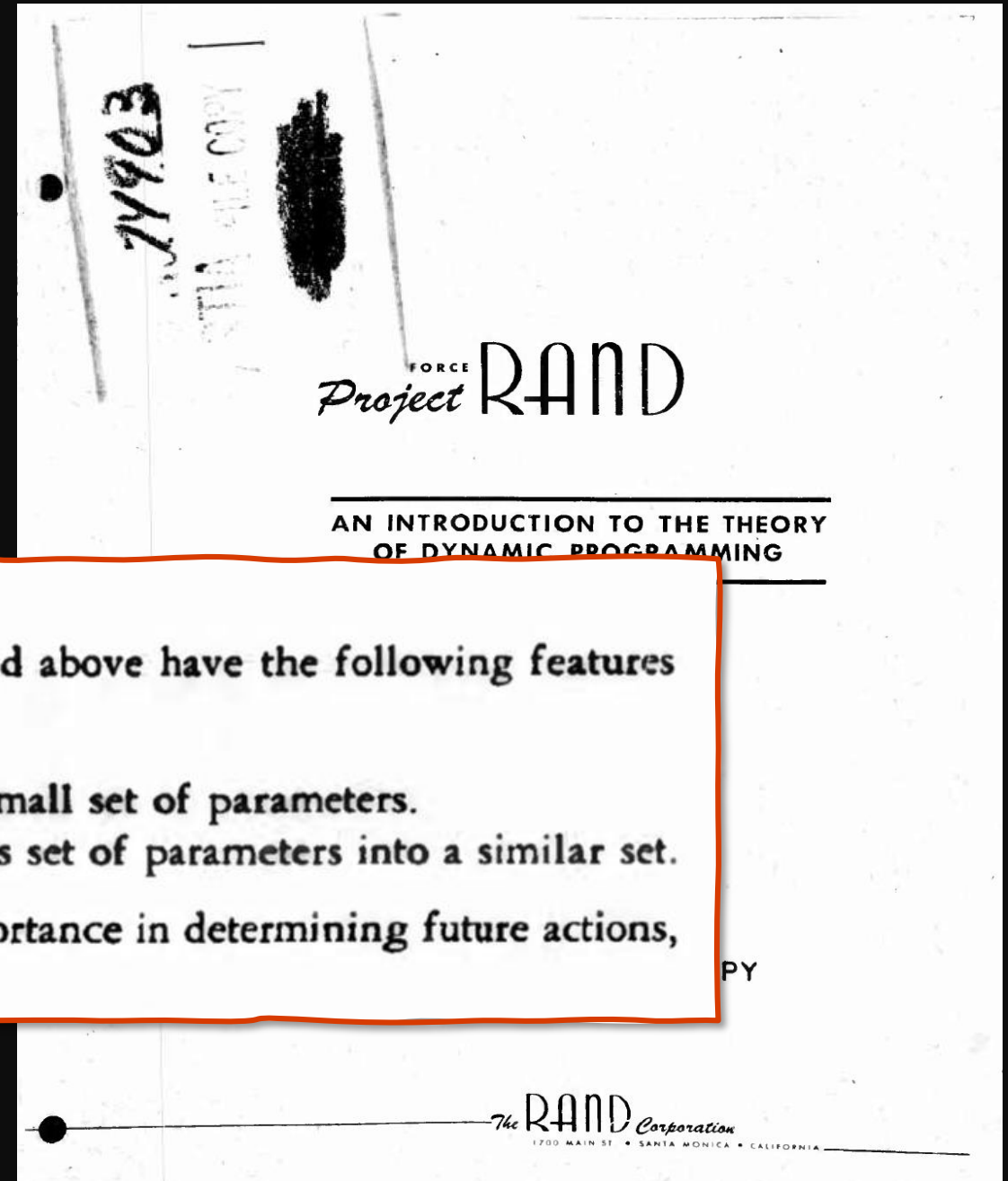
Markov Decision Processes (MDPs)

1.6. The Functional Equation Approach:

Let us begin by observing that the problems posed above have the following features in common:

1. The state of the system is described by a small set of parameters.
2. The effect of a decision is to transform this set of parameters into a similar set.
3. The past history of the system is of no importance in determining future actions, a Markovian property.

[Bellman 1953, 1954, 1957; Puterman 1994]



Markov Decision Processes (MDPs)



agent
with a (learnable)
behaviour policy



environment
with initially unknown
dynamics and reward

Markov Decision Processes (MDPs)



Markov Decision Processes (MDPs)



Markov Decision Processes (MDPs)



Markov Decision Processes (MDPs)



Optimality in Markov Decision Processes

Finite-horizon:

$$\mathbb{E} \left(\sum_{t=0}^h r_t \right)$$

Infinite-horizon:

$$\mathbb{E} \left(\sum_{t=0}^{\infty} \gamma^t r_t \right)$$

Average-reward:

$$\lim_{h \rightarrow \infty} \mathbb{E} \left(\frac{1}{h} \sum_{t=0}^h r_t \right)$$

Learning performance

Asymptotic convergence:

$$\pi_n \rightarrow \pi^* \text{ as } n \rightarrow \infty$$

PAC:

$$P(N_{errors} > F(\cdot, \epsilon, \delta)) \leq \delta$$

Regret (e.g., bound B on total regret):

$$\max_j \sum_{t=0}^T r_{tj} - r_t < B$$

[Dann, Lattimore & Brunskill 2017] unify notion of PAC and regret into Uniform-PAC

Key RL challenges

- Explore – exploit
- Credit assignment
- Function approximation



2. Value Functions

Dynamic Programming and Bellman Equations

Optimal state-value function:

$$V^*(s_t) = \max_{\pi} \mathbb{E} \left(\sum_{t=0}^{\infty} \gamma^t r_t \right)$$

Bellman equation defines recursively:

$$V^{\pi}(s_t) = R(s_t, \pi(s_t)) + \gamma \sum_{s_{t+1}} T(s_{t+1} | s_t, \pi(s_t)) V^{\pi}(s_{t+1})$$

Bellman optimality equation = Bellman eq for π^*

$$V^{\pi^*}(s_t) = \max_a R(s_t, a) + \gamma \sum_{s_{t+1}} P(s_{t+1} | s_t, a) V^{\pi}(s_{t+1})$$

[Bellman 1957]

Temporal Difference (TD) Error and TD(0)

Observe samples $\langle s_t, a_t, r_t, s_{t+1} \rangle$. If value estimates are accurate, the following must hold:

$$V(s_t) = r_t + \gamma V(s_{t+1})$$

If not, there is an error (TD error):

$$\delta = r_t + \gamma V(s_{t+1}) - V(s_t)$$

To learn better estimates – minimize δ (TD(0)):

$$V(s) \leftarrow V(s) + \alpha (r_t + \gamma V(s_{t+1}) - V(s_t))$$

TD-Gammon

Artificial Intelligence Accomplishment | 1990s

IBM researchers: [Gerald Tesauro](#)

Where the work was done: T.J. Watson Research Center

What we accomplished: Gerald Tesauro (pictured) developed an innovative combination of nonlinear function approximation with reinforcement learning (RL) techniques and showed it could achieve success in large-scale complex decision making problems. The approach was tested in a self-teaching backgammon program called TD-Gammon. Starting from a random initial strategy, and learning its strategy almost entirely from self-play, TD-Gammon achieved a remarkable level of performance. When operating without any lookahead search, it demonstrated a highly sophisticated sense of positional judgement rivaling that of human masters. When its positional evaluation was augmented by very shallow (2-ply, 3-ply) search procedures, the program matched and ultimately surpassed the playing ability of world-champion human players. This achievement has been highly influential in the AI and computer gaming communities, and has inspired numerous real-world applications of similar RL techniques.

Related links: [Temporal difference learning and TD-Gammon](#), March 1995 paper in Communications of the ACM.

Image credit: IBM Think Magazine, December 1992

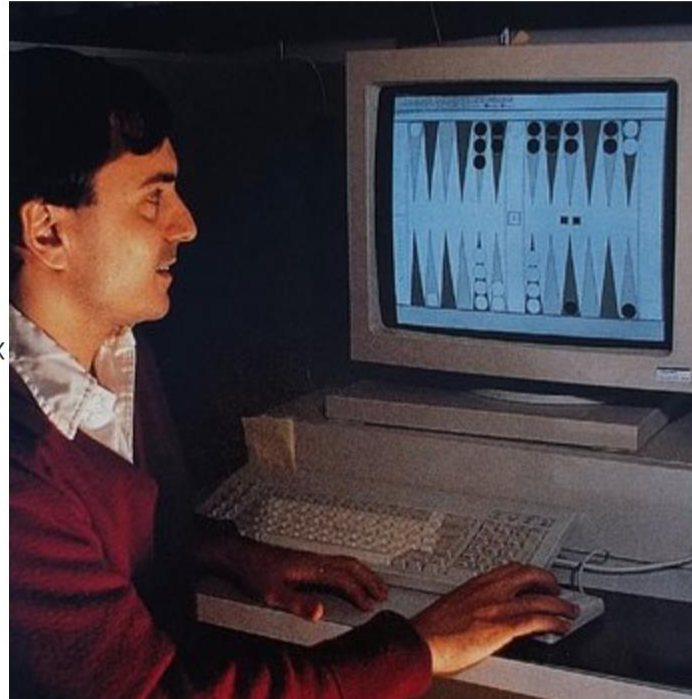


Image credit:

<https://en.wikipedia.org/wiki/TD-Gammon>

Credit: IBM Research

https://researcher.watson.ibm.com/researcher/view_page.php?id=6853

Q-Learning

Bellman optimality equation for Q:

$$Q^*(s_t, a_t) = \mathbb{E}_{\pi^*} \left(r_t + \gamma \max_a Q^*(s_{t+1}, a) \right)$$

$$\delta = r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a)$$

Q-Learning Algorithm

For each episode:

Observe initial state s_0

for each step $t = 0, 1, 2 \dots$ in the episode:

Select action a_t using $Q(a, s)$ (e.g., ϵ -greedy)

Take action a_t , observe r_t, s_{t+1}

$$Q(s_t, a_t) = Q(s_t, a_t) + \alpha[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a)]$$

$$s = s_{t+1}$$

[Watkins, 1989; Dayan & Watkins, 1992]

Regret bounds for Q-Learning:

Chi Jin, Allen-Zhu, Bubeck & Jordan: "Is q-learning provably efficient?" NeurIPS 2018

Project Malmo

A platform for AI experimentation, built on Minecraft

microsoft.com/en-us/research/project/project-malmo/

Open source on github
github.com/Microsoft/malmo

[Johnson, Hofmann, Hutton & Bignell, 2016]



Microsoft / **malmo** Unwatch 233 Unstar 1,998 Fork 263

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Project Malmo is a platform for Artificial Intelligence experimentation and research built on top of Minecraft. We aim to inspire a new generation of research into challenging new problems presented by this unique environment. --- For installation instructions, scroll down to **Getting Started** below, or visit the project page for more information: <https://www.microsoft.com/en-us/research/project/project-malmo/> — Edit

695 commits 4 branches 10 releases 11 contributors

Branch: master New pull request Create new file Upload files Find file Clone or download

timhutton committed on GitHub Merge pull request #300 from Microsoft/xerces_init Latest commit efcd5b4 3 days ago

.travis	Minor: removed comments.	20 days ago
ALE_ROMS	Applied MIT license.	2 months ago
Malmo	Fix: having two agent_host's in the same script causes a crash becaus...	4 days ago
Minecraft	Fix: use and attack in discrete movement were being sent to first pla...	4 days ago
Schemas	Fix: time 0 was invalid yet suggested in the documentation.	4 days ago
cmake	Fix: changes to make Lua work on Fedora 23.	2 months ago
doc	Minor: fixed item numbering.	5 days ago
sample_missions	Making cliff_walking_1.xml use discrete actions.	a month ago

Q-Learning in Malmo



Task: navigate an initially unknown environment

Adapted from Sutton & Barto (2018) chapter 6

Try this at home, see <https://github.com/Microsoft/malmo> - tutorial 6

Q-Learning in Malmo: Task Definition



Positive reward

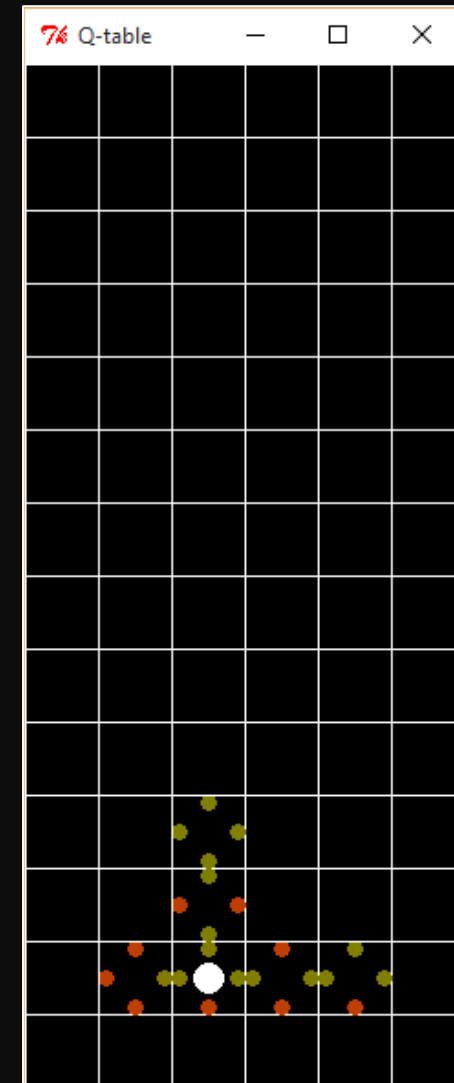
Negative reward

Task: navigate an initially unknown environment

Adapted from Sutton & Barto (2018) chapter 6

Try this at home, see <https://github.com/Microsoft/malmo> - tutorial 6

Q-Learning in Malmo: Q-table



Try this at home, see <https://github.com/Microsoft/malmo> - tutorial 6

Q-Learning in Malmo: Initial policy



The agent has to explore to learn about consequences of it's actions

Try this at home, see <https://github.com/Microsoft/malmo> - tutorial 6

Q-Learning in Malmo:



Try this at home, see <https://github.com/Microsoft/malmo> - tutorial 6

3. Function Approximation

Q-Learning with Function Approximation

To generalize over states and actions, parameterize Q with a function approximator, e.g., a deep neural net:

$$\delta = r_t + \gamma \max_a Q(s_{t+1}, a; \theta) - Q(s_t, a; \theta)$$

Turn into an optimization problem by minimizing the loss on the TD error:

$$\begin{aligned} J(\theta) &= \|\delta\|^2 \\ &= \left\| r_t + \gamma \max_{a \in A} Q(s_{t+1}, a; \theta) - Q(s_t, a_t; \theta) \right\|^2 \end{aligned}$$

Stability

The “deadly triad” [Sutton & Barto, 2018]

- 1) Off-policy learning
- 2) Flexible function approximation
- 3) Bootstrapping

In the face of all three, learning is unstable (can and will diverge) [Baird 1995; Tsitsiklis & Van Roy 1997]

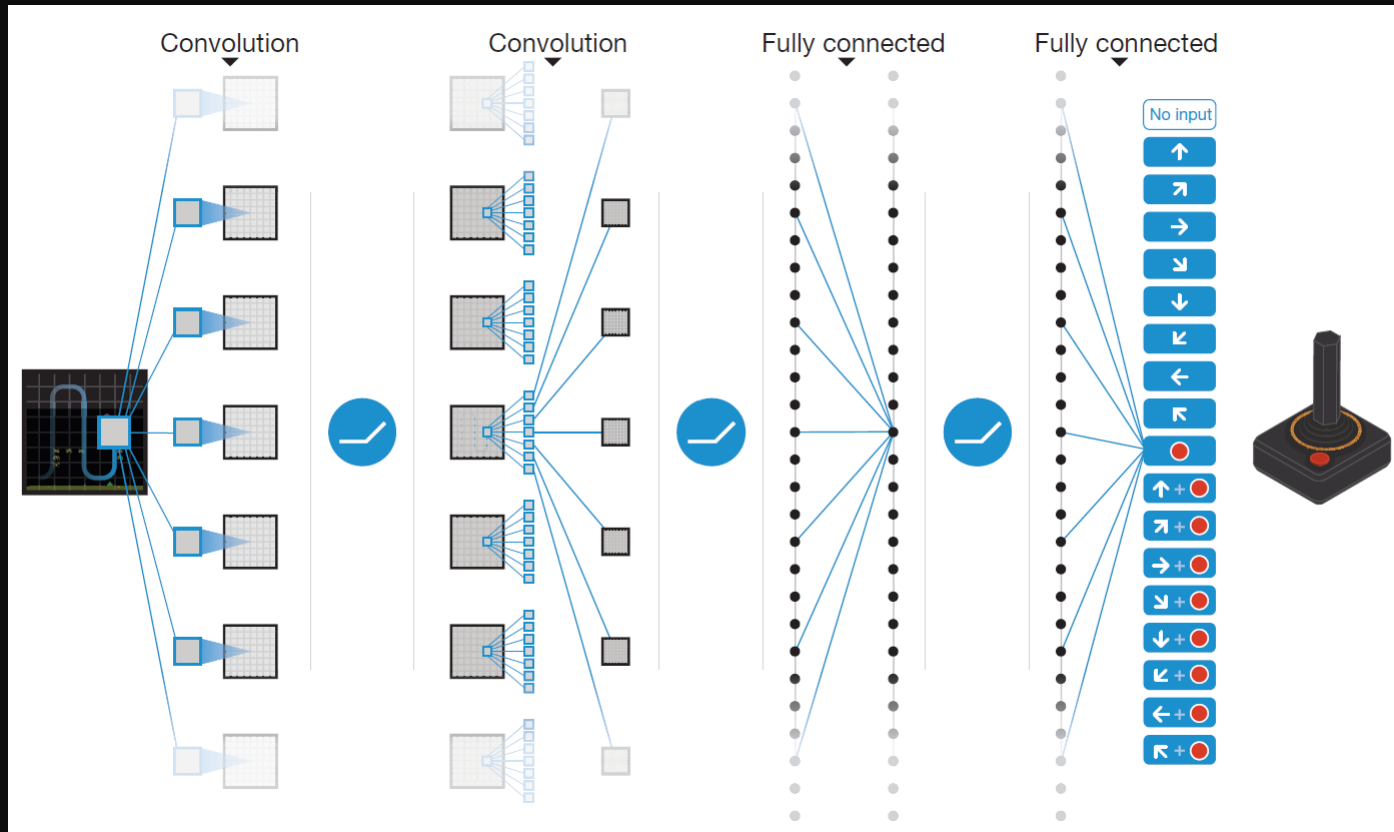
DQN [Mnih et al. 2013, 2015] stabilizes learning:

- 1) Experience replay buffer [Lin 1993] + mini-batch SGD
- 2) Separate target network stabilizes optimization targets: $\delta = r_t + \gamma \max_{a \in A} Q(s_{t+1}, a; \theta') - Q(s_t, a_t; \theta)$
- 3) Clip δ to $[-1, 1]$

Great blog post with code (DQN, Double DQN):

<https://davidsanwald.github.io/2016/12/11/Double-DQN-interfacing-OpenAi-Gym.html>

Results



Figures from [Mnih et al. 2015]. Training setup across all 49 Atari games (above); Results in terms of human-normalized scores (right)

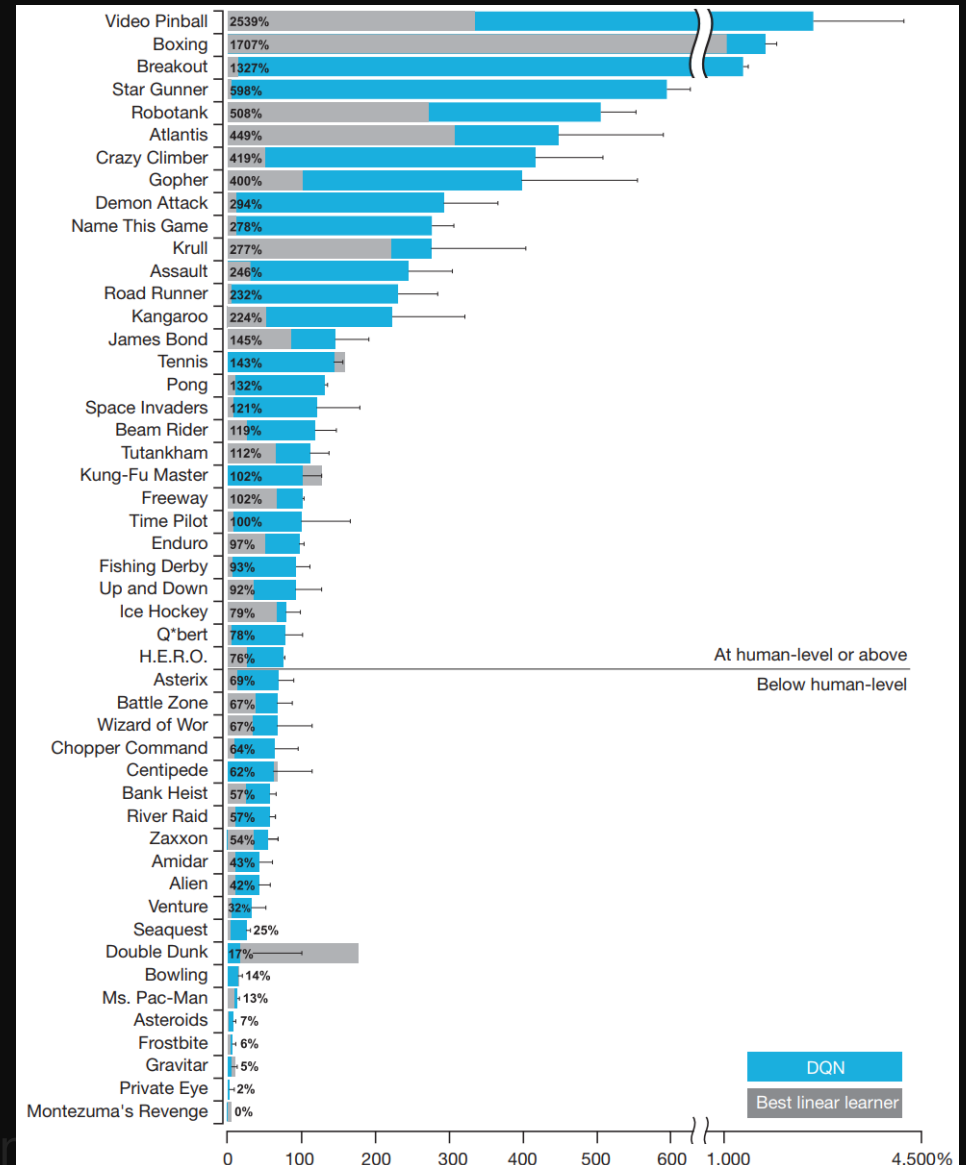


Figure from: Mnih et al. 2015

Improving DQN (Selection)

[Van Hasselt et al. 2016] Double Q-Learning – reduce bias

[Anschel et al. 2017] Average Q-Learning – reduce variance

[Andrychowicz et al. 2017] Hindsight Experience replay

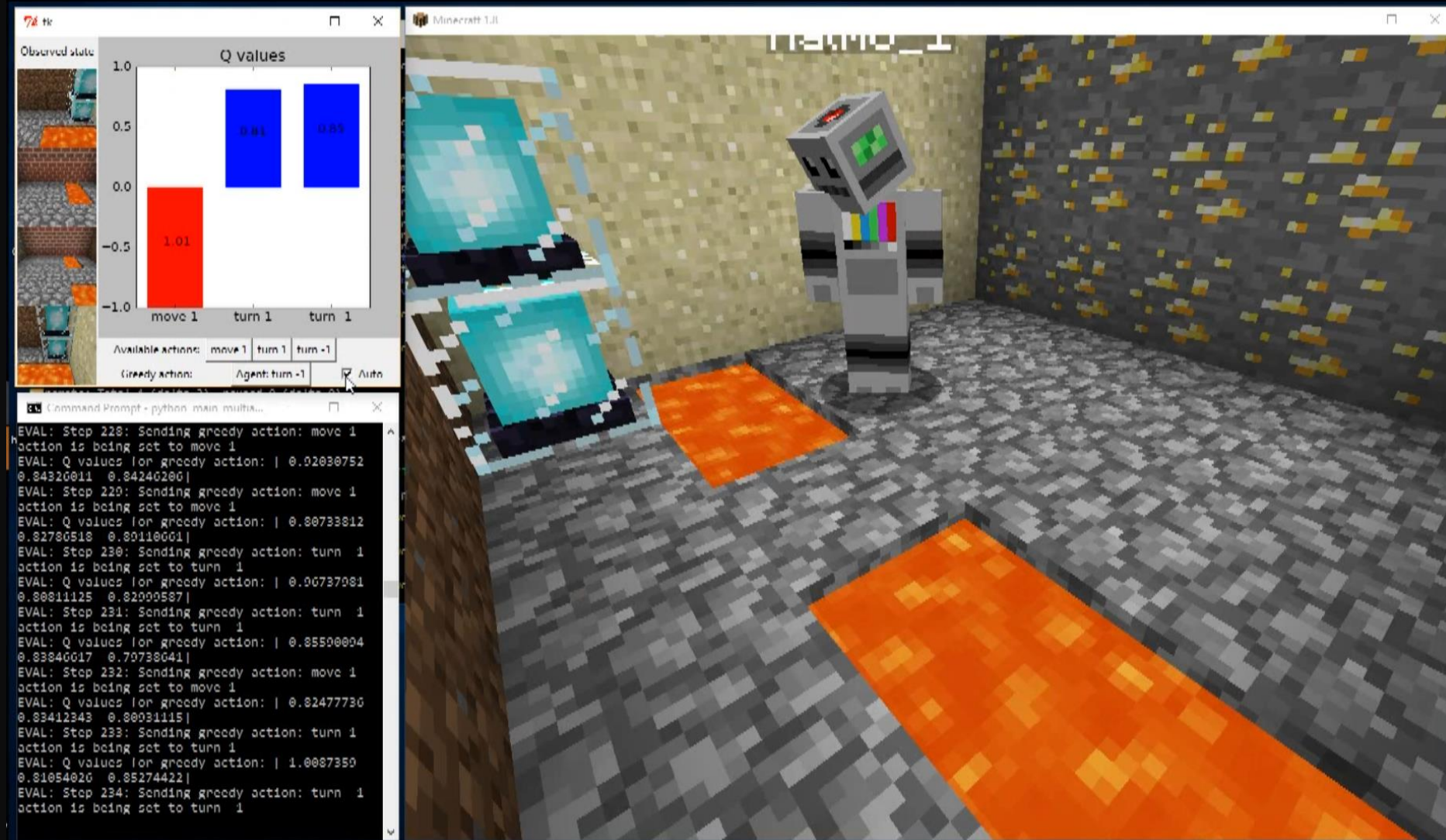
[Dabney et al. 2018] Distributional RL (quantile regression)

[Horgan et al. 2018] **Ape-X** – distributed replay buffer

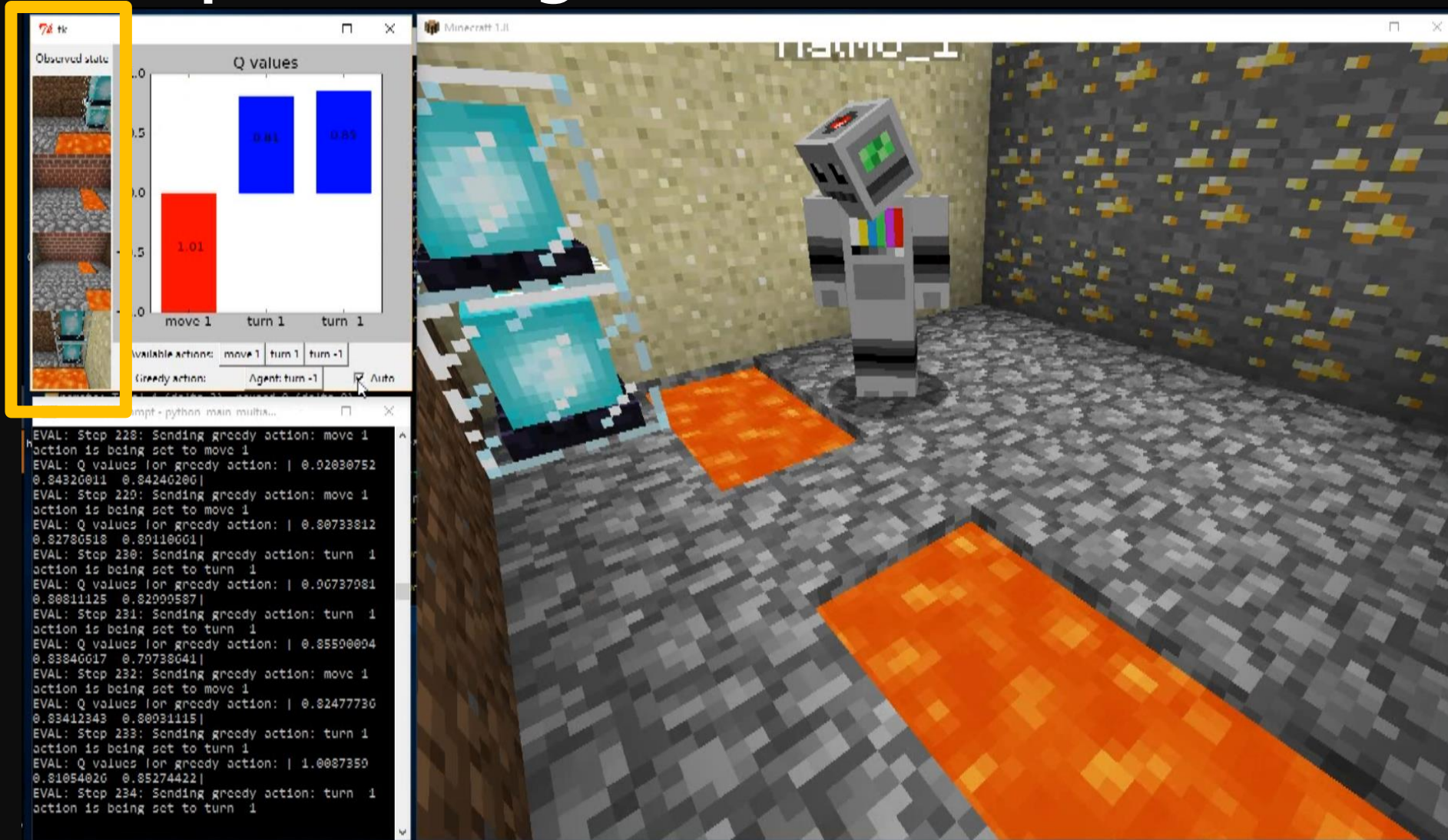
For further study check David Silver's ICML 2016:

https://www.icml.cc/2016/tutorials/deep_rl_tutorial.pdf

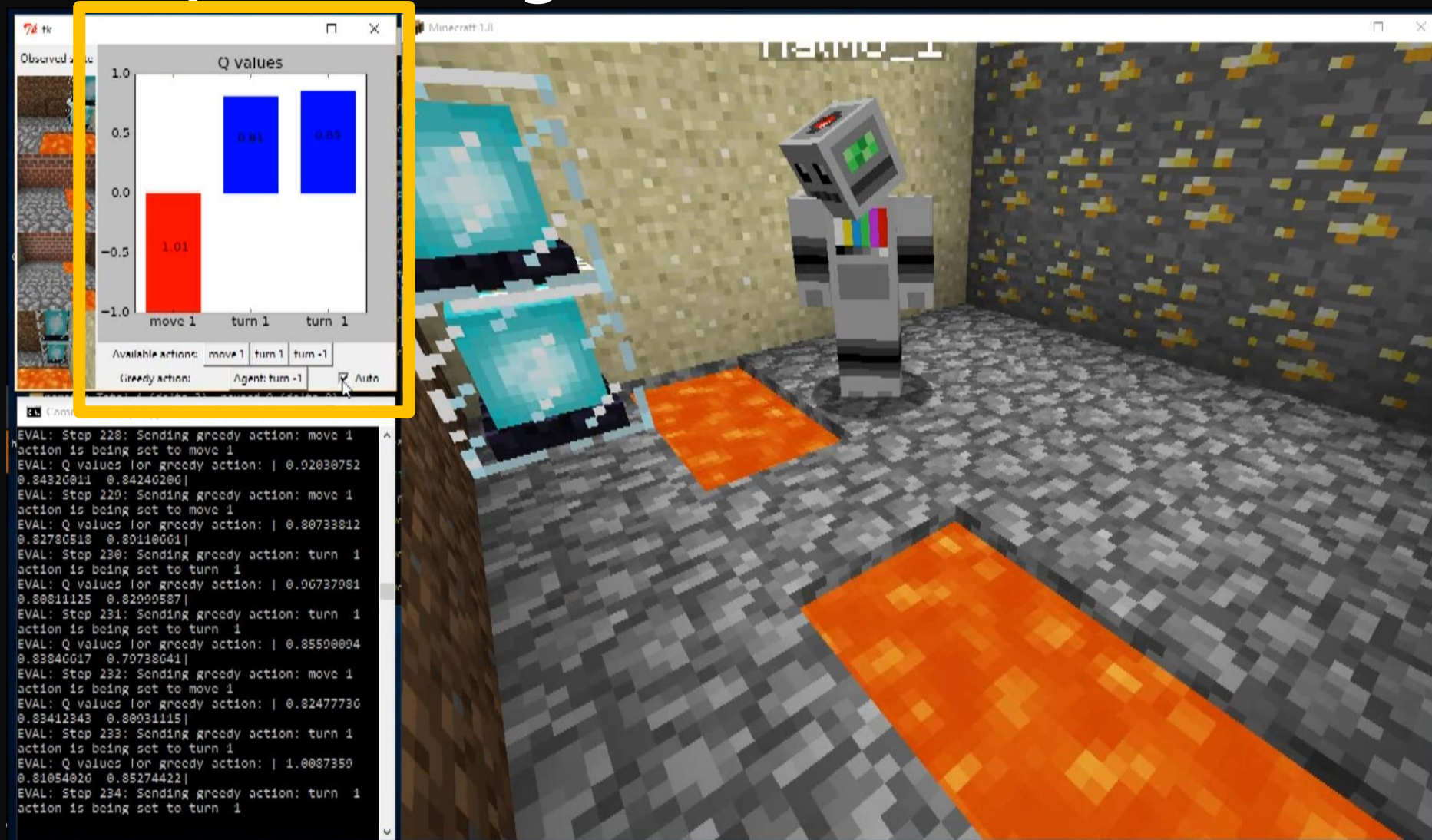
Case Study: Learning to navigate Minecraft from pixels using DQN



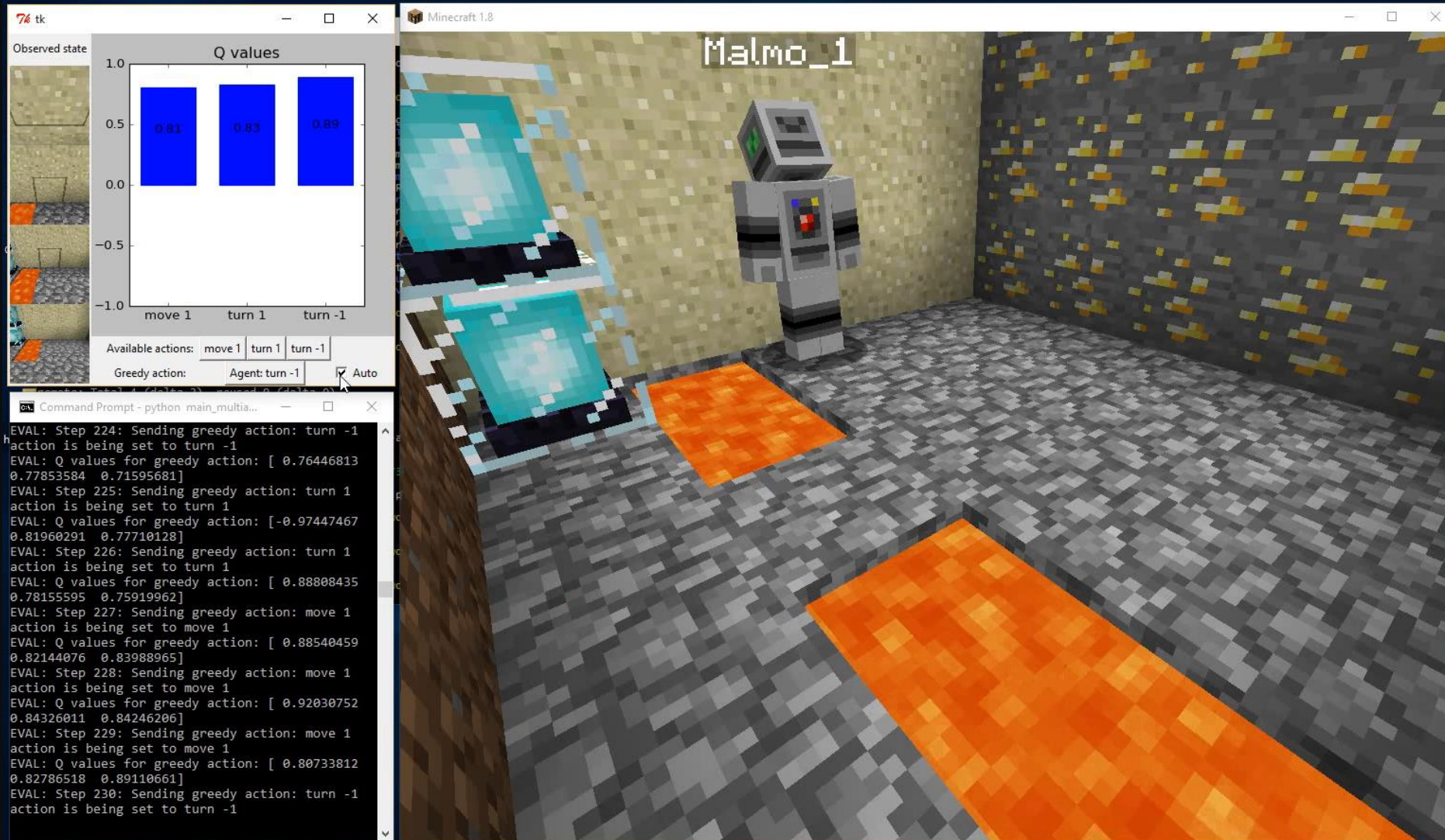
Case Study: Learning to navigate Minecraft from pixels using DQN



Case Study: Learning to navigate Minecraft from pixels using DQN



Case Study: Learning to navigate Minecraft from pixels using DQN

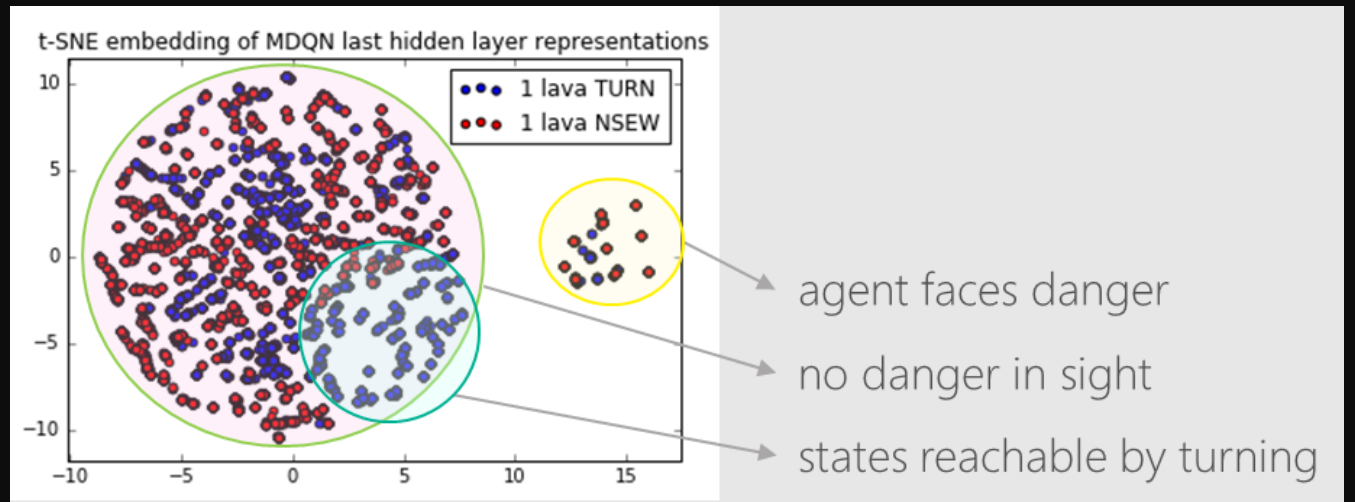
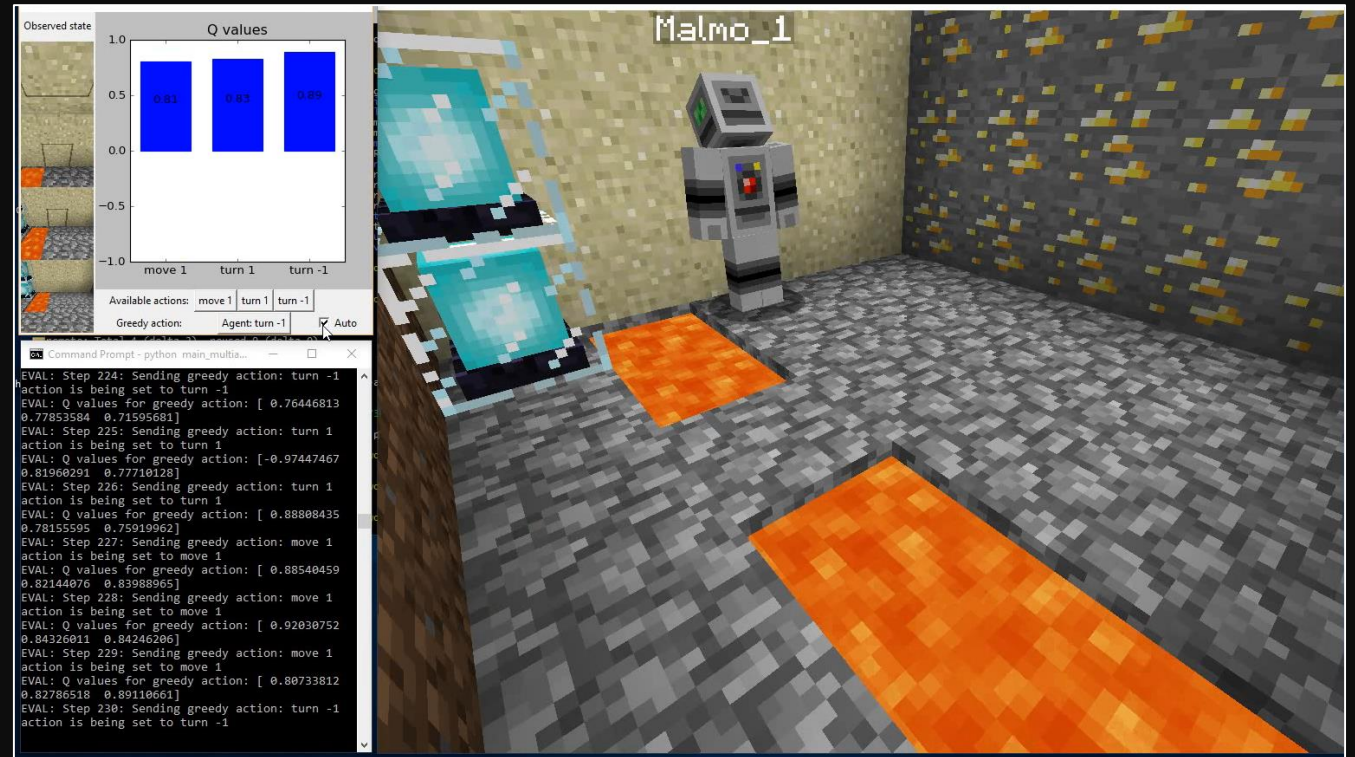
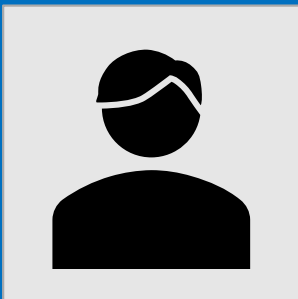


Decoding multitask DQN in the world of Minecraft

Lydia Liu, Urun Dogan,
Katja Hofmann

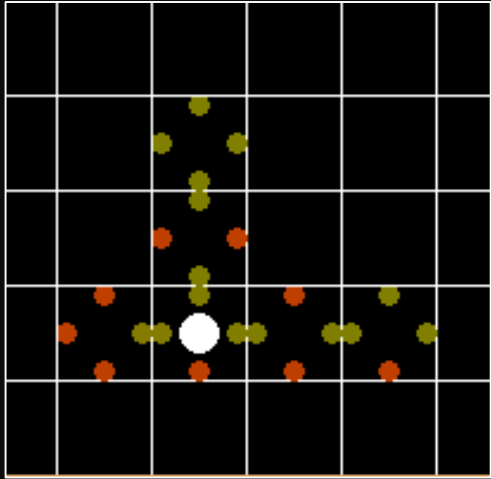
EWRL 2016

Deep Learning Workshop @ NIPS 2016



3. Exploration

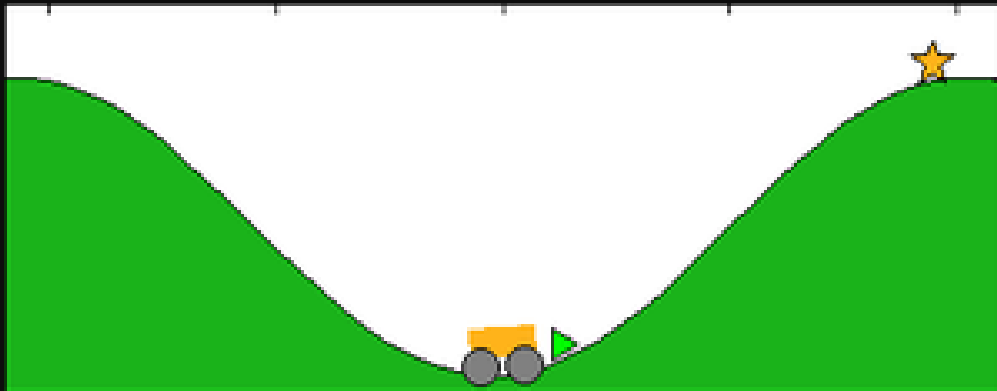
Exploration vs Exploitation – Common Approaches



Optimistic initialization

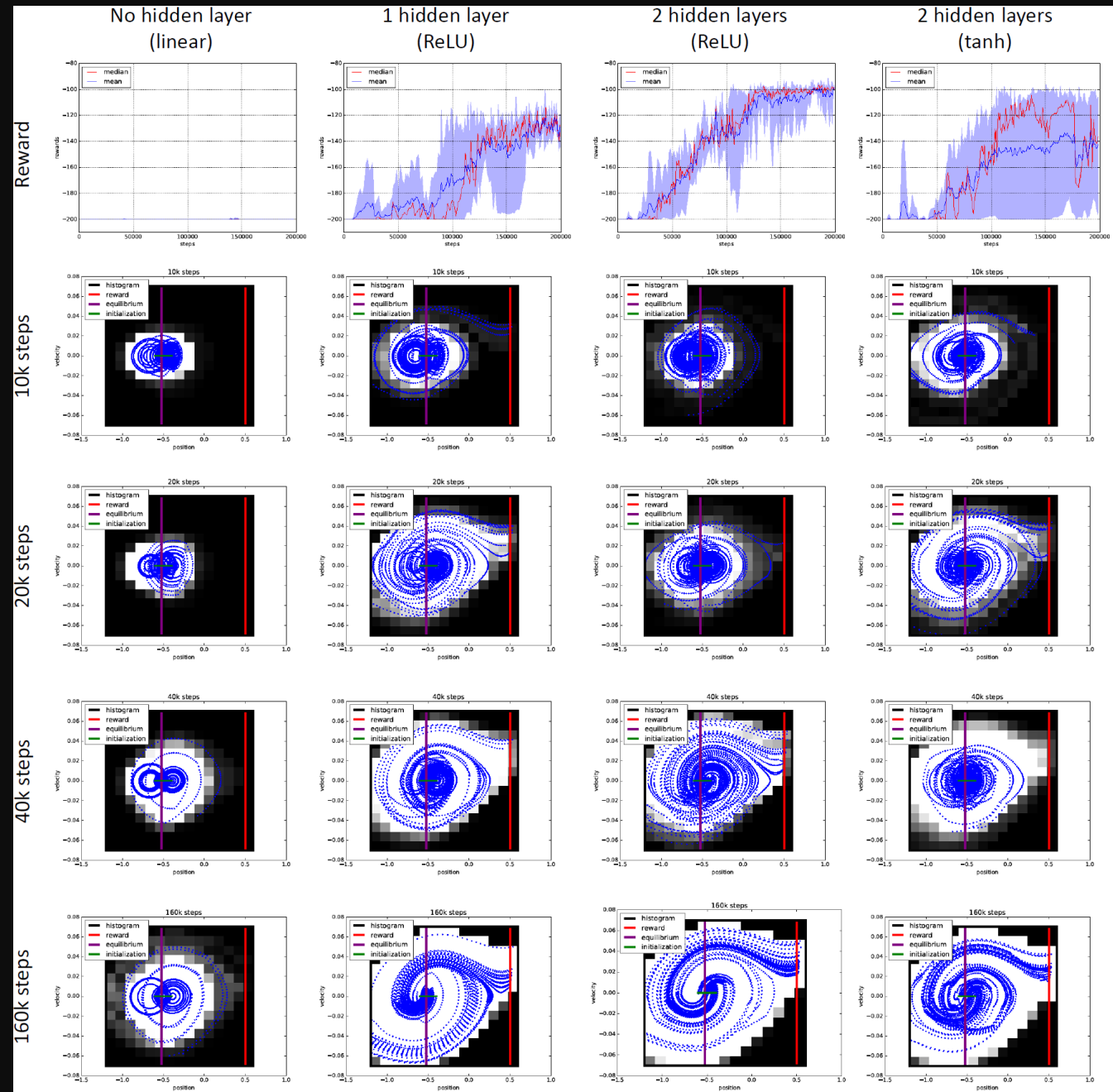
If upper bound is known (e.g., on Q), initialize all estimates to the upper bound.

Example: Interaction between optimistic initialization and function approximation

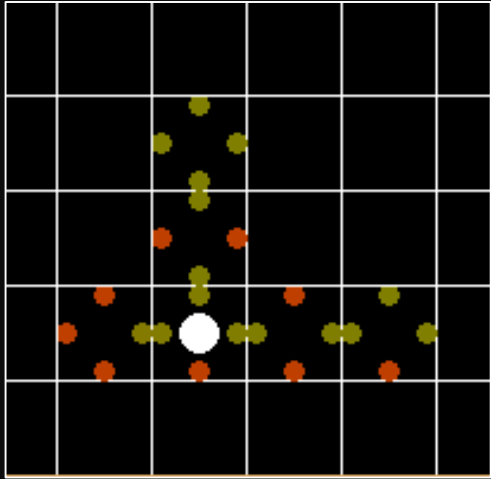


https://en.wikipedia.org/wiki/Mountain_car_problem

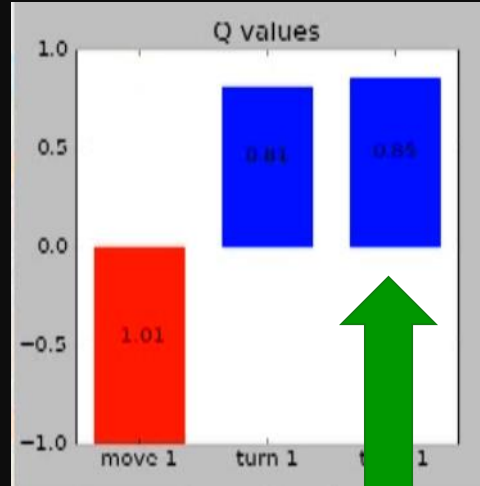
[Dauparas, Tomioka & Hofmann, 2018]



Exploration vs Exploitation – Common Approaches



Optimistic
initialization

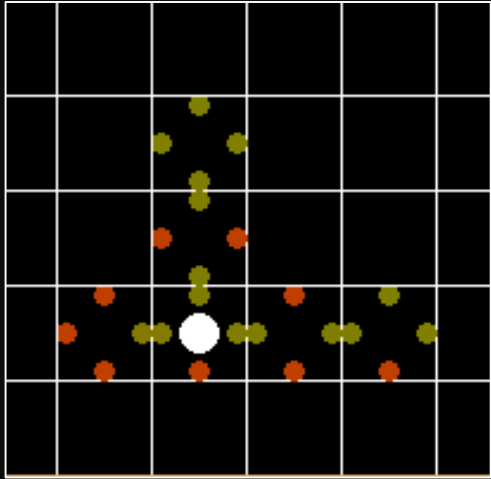


"greedy" action

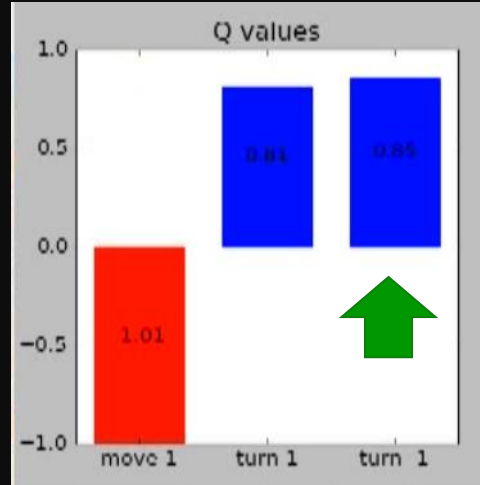
Epsilon-greedy

$$\pi_t = \begin{cases} \underset{a \in A}{\operatorname{argmax}} \hat{r}_t(a) & w. prob. 1 - \varepsilon \\ rand(a) & w. prob. \varepsilon \end{cases}$$

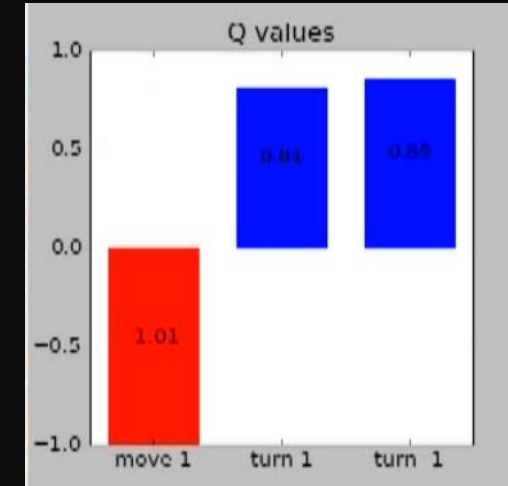
Exploration vs Exploitation – Common Approaches



Optimistic
initialization



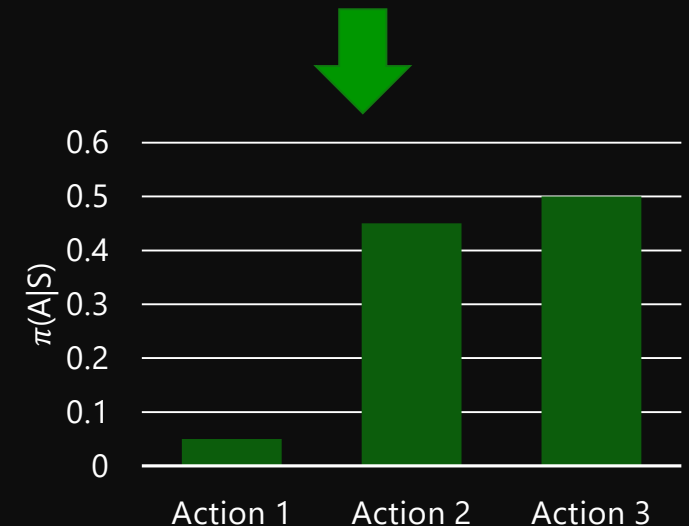
Epsilon-
greedy



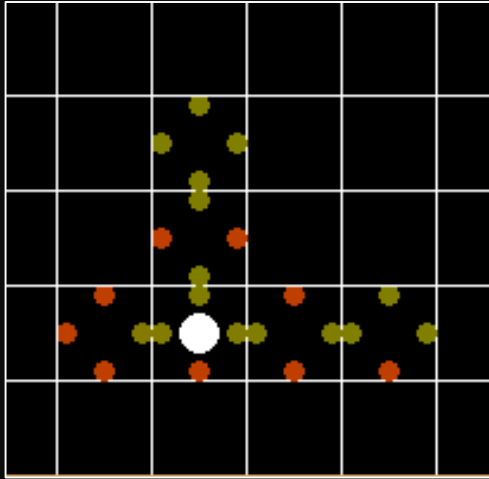
**Soft-
max**

Sample from the Softmax policy:

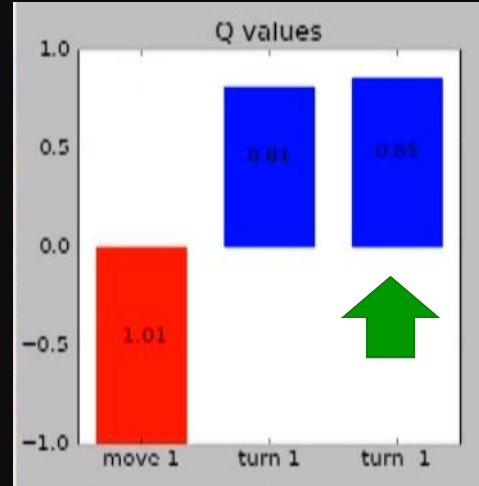
$$\pi(a|s) = \frac{e^{h(s,a)}}{\sum_{a' \in A} e^{h(s,a')}}$$



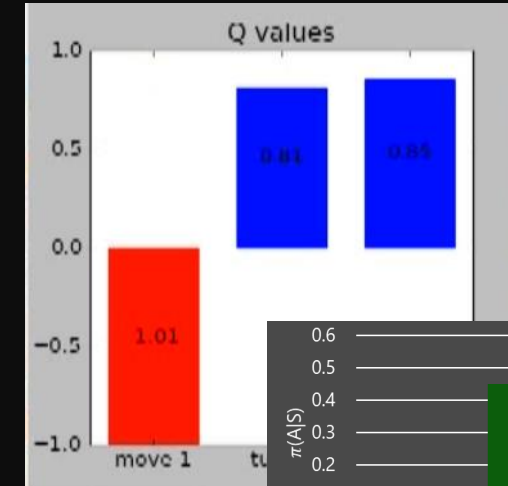
Exploration vs Exploitation – Optimistic initialization



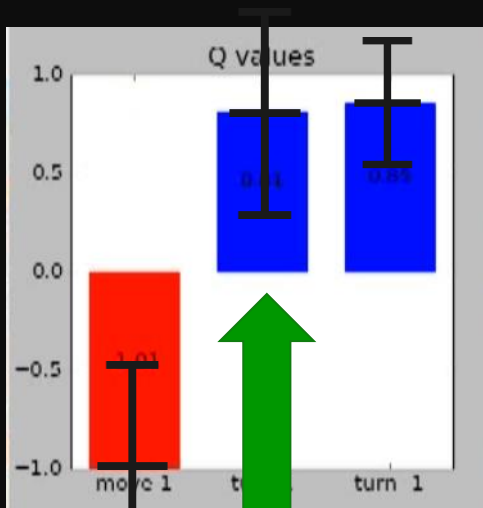
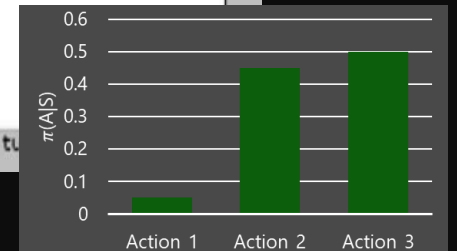
Optimistic
initialization



Epsilon-
greedy



Softmax



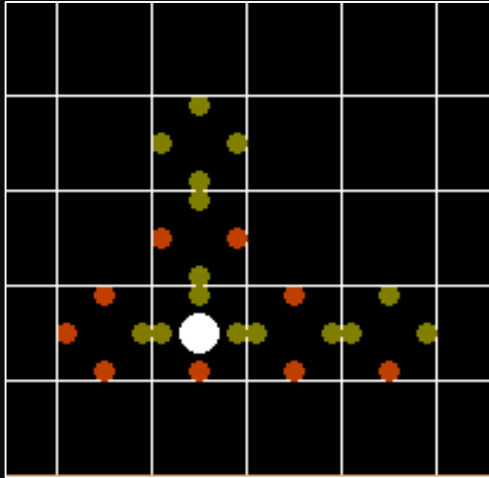
**Upper
confidence
bound**

Derive Upper Confidence Bound (UCB), e.g., for bandits:

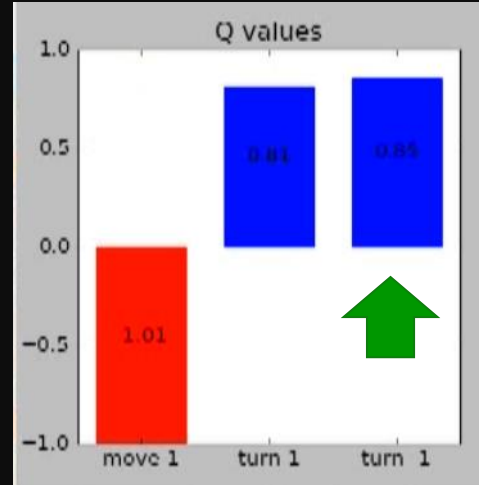
$$\pi_t = \operatorname{argmax}_{a \in A} \hat{r}_t(a) + c \sqrt{\frac{\ln t}{N_t(a)}}$$

[Auer et al. '02]

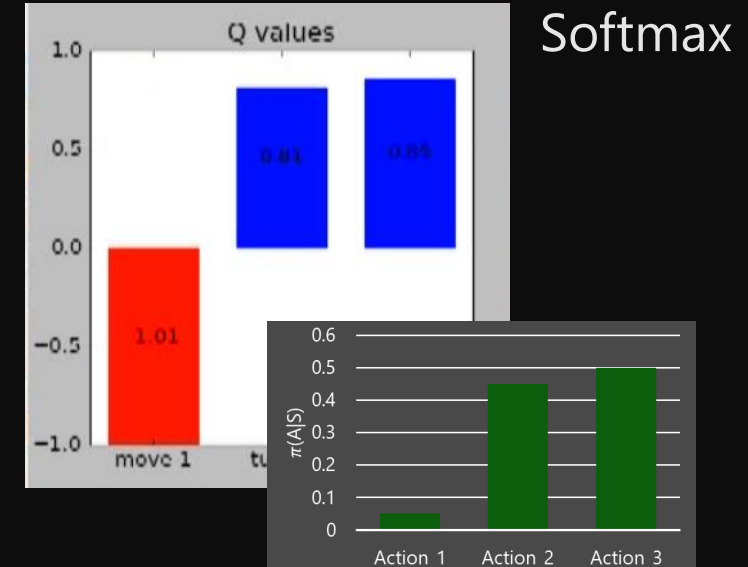
Exploration vs Exploitation – Optimistic initialization



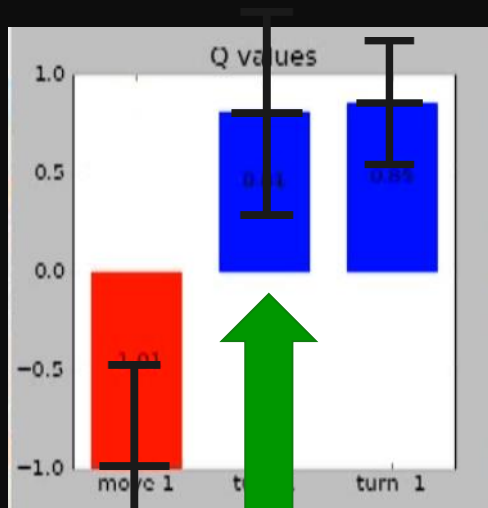
Optimistic initialization



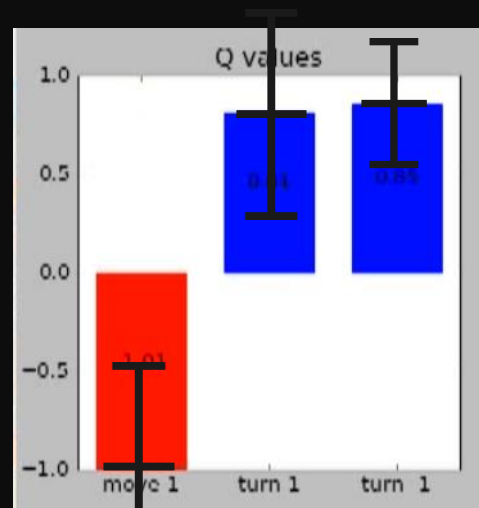
Epsilon-greedy



Softmax



Upper confidence bound

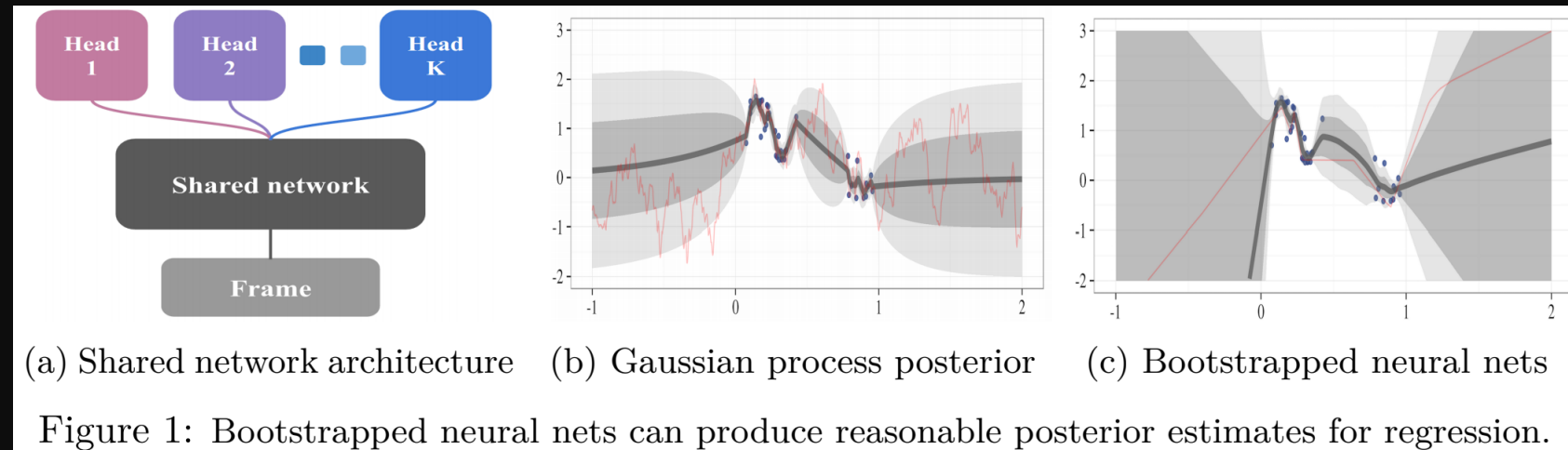


Posterior sampling

Maintain distribution $P(r|a)$. At time t sample from this distribution, and take the optimal action according to the sample; update P .

Deep exploration using Bootstrapped DQN

Idea (BDQN):
Approximate
uncertainty over Q
using deep ensembles
[Osband et al. 2016]



[Osband et al. 2018]
extend BDQN with
randomized prior
function

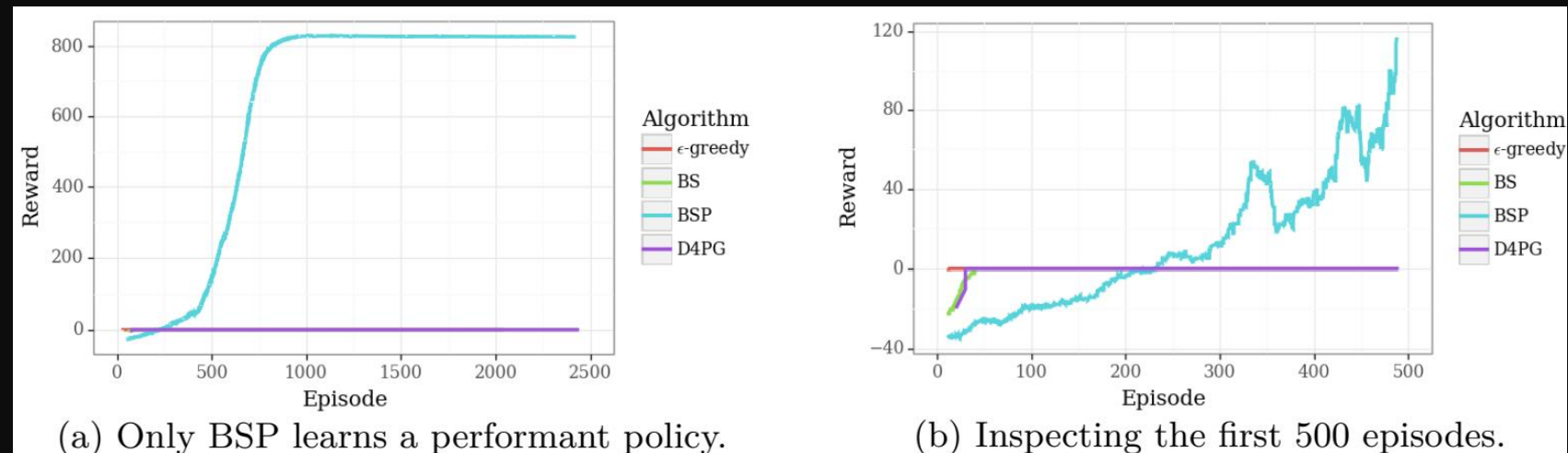


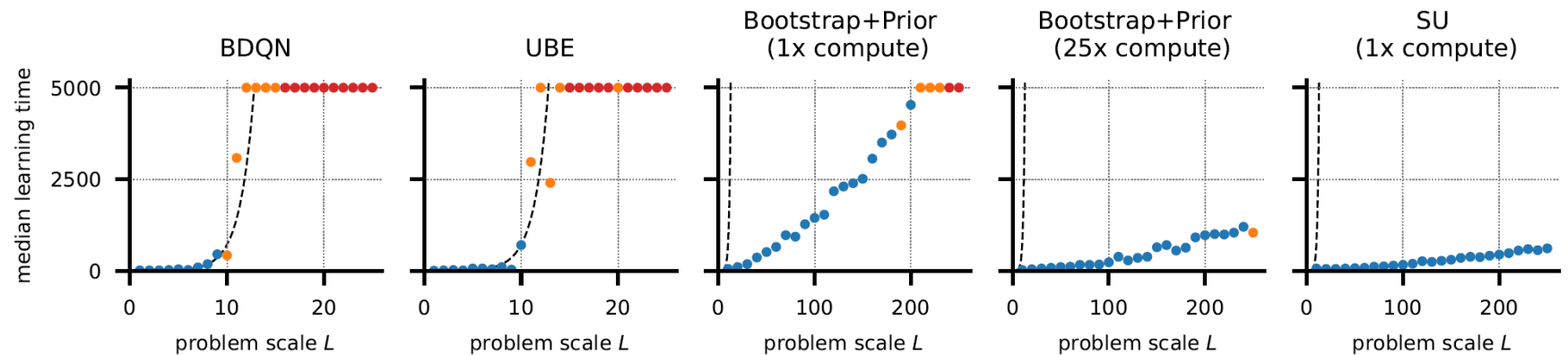
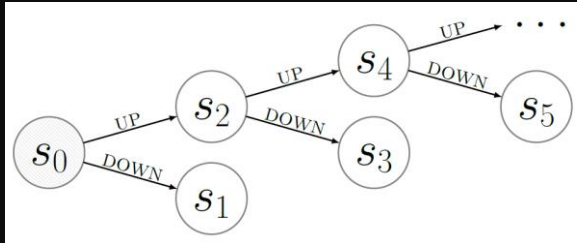
Figure 5: Learning curves for the modified cartpole swing-up task.

Successor Uncertainties

Idea: approximate uncertainty over Q as a function of successor features
[Dayan 1993]

Objective:
$$\underbrace{|\langle \phi_t, w \rangle - r_{t+1} - \langle \psi_{t+1}, w \rangle|^{-2}}_{\text{standard } Q \text{ value loss}} + \underbrace{\|\psi_t - \phi_t - \gamma \psi_{t+1}^-\|^2}_{\text{succ. feat. regularisation}} + \underbrace{|\langle \phi_t, w \rangle - r_{t+1}|^2}_{\text{reward prediction loss}}$$

Results: chain
MDP

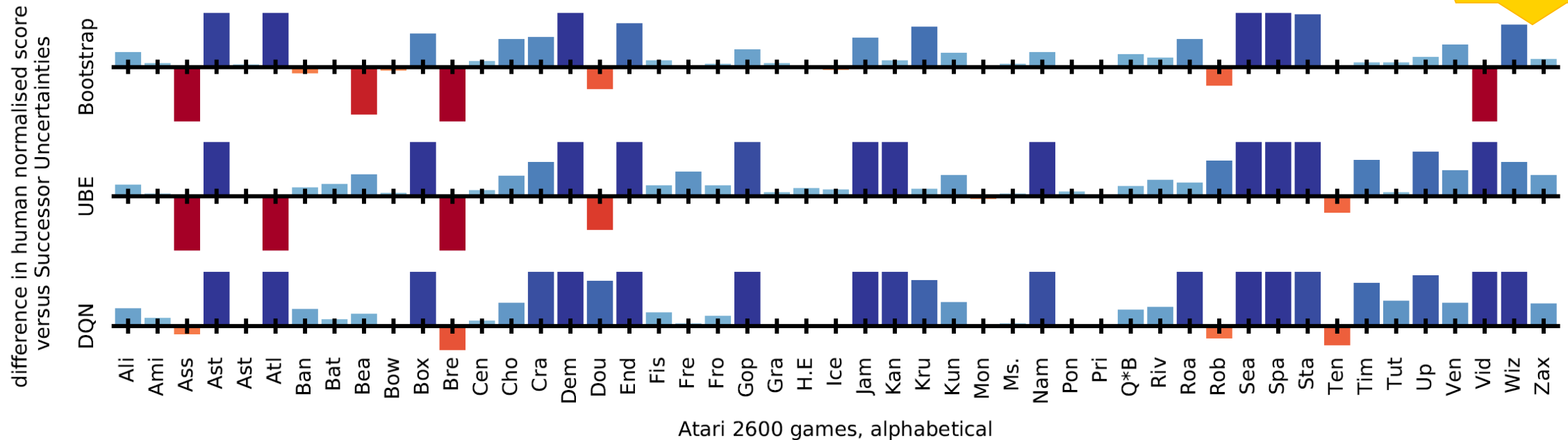


Median # episodes to solve the tree MDP (5 seeds). Blue = all (5), orange = some (1-4), red = none of the 5 runs finished within 5000 episodes. Dashed line for uniform policy. Note the varying x-axis scale!

[Janz*, Hron*, Mazur, Hofmann, Hernández-Lobato, Tschitschek, NeurIPS 2019]

Successor Uncertainties

Tue 10:45a
#198



Bars show the difference in human normalised score between SU and BootDQN (top), UBE (middle) and DQN (bottom) for each of the 49 Atari 2600 games. Blue indicates SU performed better, red worse. SU outperforms the baselines on 36/49, 43/49 and 42/49 games respectively. Y-axis clipped to $[-2.5, 2.5]$.

[Janz*, Hron*, Mazur, Hofmann, Hernández-Lobato, Tschitschek, NeurIPS 2019]

4. Policy Gradient and Actor Critic Approaches

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_\theta(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k$$

$$\hat{A}_i = R_i - b$$

$$\theta = \theta + \alpha \nabla_\theta \log \pi_\theta(a|s_i) \hat{A}_i$$

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_{\theta}(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k$$

$$\hat{A}_i = R_i - b$$

$$\theta = \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a|s_i) \hat{A}_i$$



Policy
parameterized by
learnable θ

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_{\theta}(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k \longrightarrow \text{Unbiased estimate of remaining episode return under } \pi_{\theta} \text{ starting from } i$$

$$\hat{A}_i = R_i - b$$

$$\theta = \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a|s_i) \hat{A}_i$$

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_{\theta}(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k$$

$$\hat{A}_i = R_i - b \longrightarrow$$

$$\theta = \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a|s_i) \hat{A}_i$$

Subtract baseline b to lower variance,
e.g., episode return $R = \sum_1^t r_t$ (intuition:
advantage)

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_{\theta}(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k$$

$$\hat{A}_i = R_i - b$$

$$\theta = \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a|s_i) \hat{A}_i$$



Gradient with respect to policy
parameters estimated from samples

[Williams 1992]

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_{\theta}(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k$$

$$\hat{A}_i = R_i - b$$

$$\theta = \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a|s_i) \hat{A}_i$$

$\downarrow$
 $\hat{g}$

Objective: $J(\theta) = \sum_{\tau} P_{\theta}(\tau) R(\tau)$

$$\begin{aligned} \nabla_{\theta} J(\theta) &= \nabla_{\theta} \sum_{\tau} P_{\theta}(\tau) R(\tau) \\ &= \sum_{\tau} \nabla_{\theta} P_{\theta}(\tau) R(\tau) \end{aligned}$$

$\hat{g}$ is an unbiased estimate: Policy gradient theorem [Sutton et al. 2000]

[Williams 1992]

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_{\theta}(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k$$

$$\hat{A}_i = R_i - b$$

$$\theta = \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a|s_i) \hat{A}_i \longrightarrow \text{Actor-critic approaches use learned estimate (e.g., } \hat{A}(s, a) = \hat{Q}(s, a) - \hat{V}(s) \text{)}$$

Policy Gradient Algorithm: REINFORCE

For each episode:

Generate $\tau = s_0, a_0, r_1, s_1, a_1, r_1 \dots s_{t-1}, a_{t-1}, r_t$ by following $\pi_{\theta}(a|s)$
for each step $i = 0 \dots t - 1$:

$$R_i = \sum_{k=i}^t \gamma^{t-k} r_k$$

$$\hat{A}_i = R_i - b$$

$$\theta = \theta + \alpha \nabla_{\theta} \log \pi_{\theta}(a|s_i) \hat{A}_i$$

NeurIPS 2016 Tutorial by Pieter Abbeel John Schulman: Deep Reinforcement Learning through Policy Optimization
(<https://media.nips.cc/Conferences/2016/Slides/6198-Slides.pdf>)

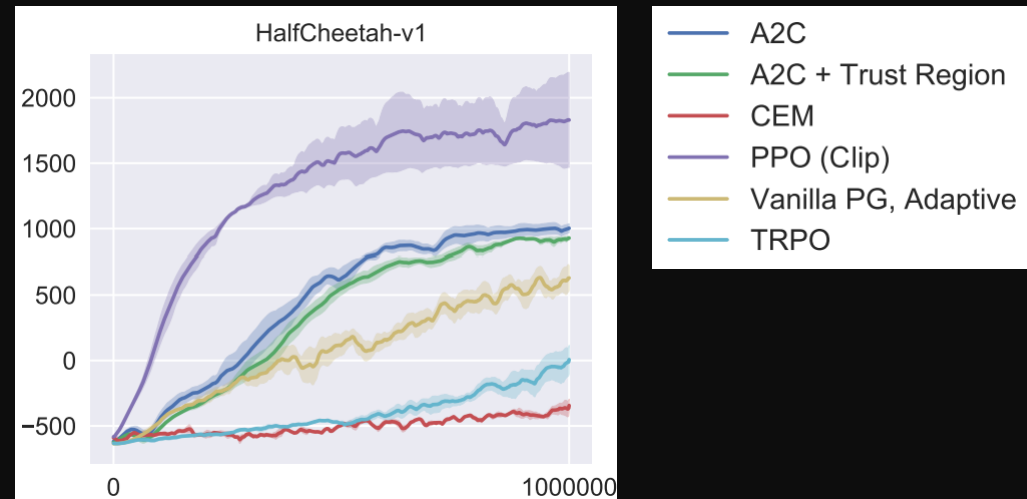
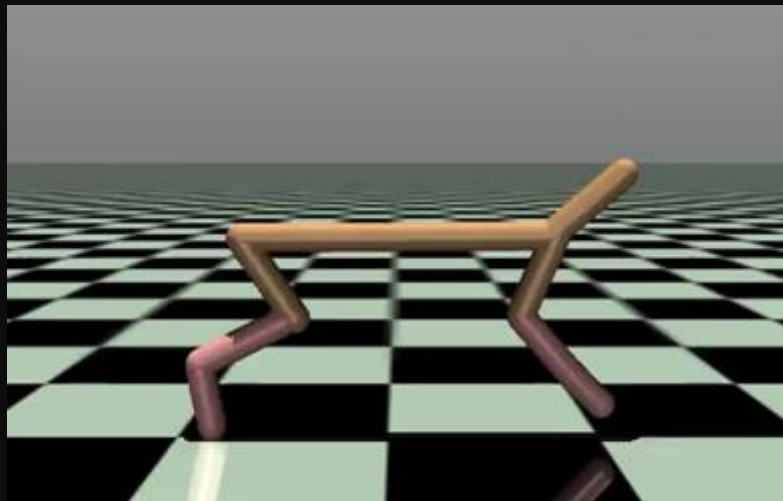
Actor-Critic with Deep Function Approximation

Need to balance between learning speed, stability

[Kakade & Langford 2002] Conservative Policy Iteration (CPI): propose surrogate objective, guarantee monotonic improvement under specific state distribution

[Schulman et al. 2015] Trust Region Policy Optimization (TRPO): approximates CPI with trust region constraint

[Schulman et al. 2017] Proximal Policy Optimization (PPO): replace TRPO constraint with KL penalty + clipping (computationally efficient)



Actor-Critic with Deep Function Approximation

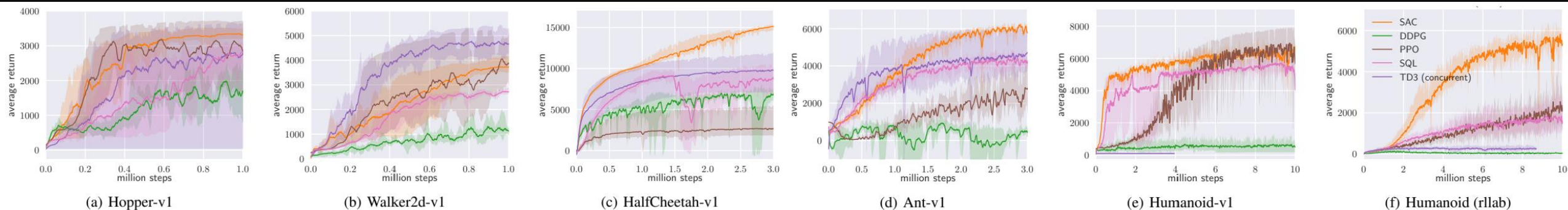
Need to balance between learning speed, stability

[Kakade & Langford 2002] Conservative Policy Iteration (CPI): propose surrogate objective, guarantee monotonic improvement under specific state distribution

[Schulman et al. 2015] Trust Region Policy Optimization (TRPO): approximates CPI with trust region constraint

[Schulman et al. 2017] Proximal Policy Optimization (PPO): replace TRPO constraint with KL penalty + clipping (computationally efficient)

[Haarnoja et al. 2018] Soft Actor-Critic (SAC): stabilize learning by jointly maximizing expected reward and policy entropy (based on maximum entropy RL [Ziebart et al. 2008])



Optimistic Actor Critic (OAC)

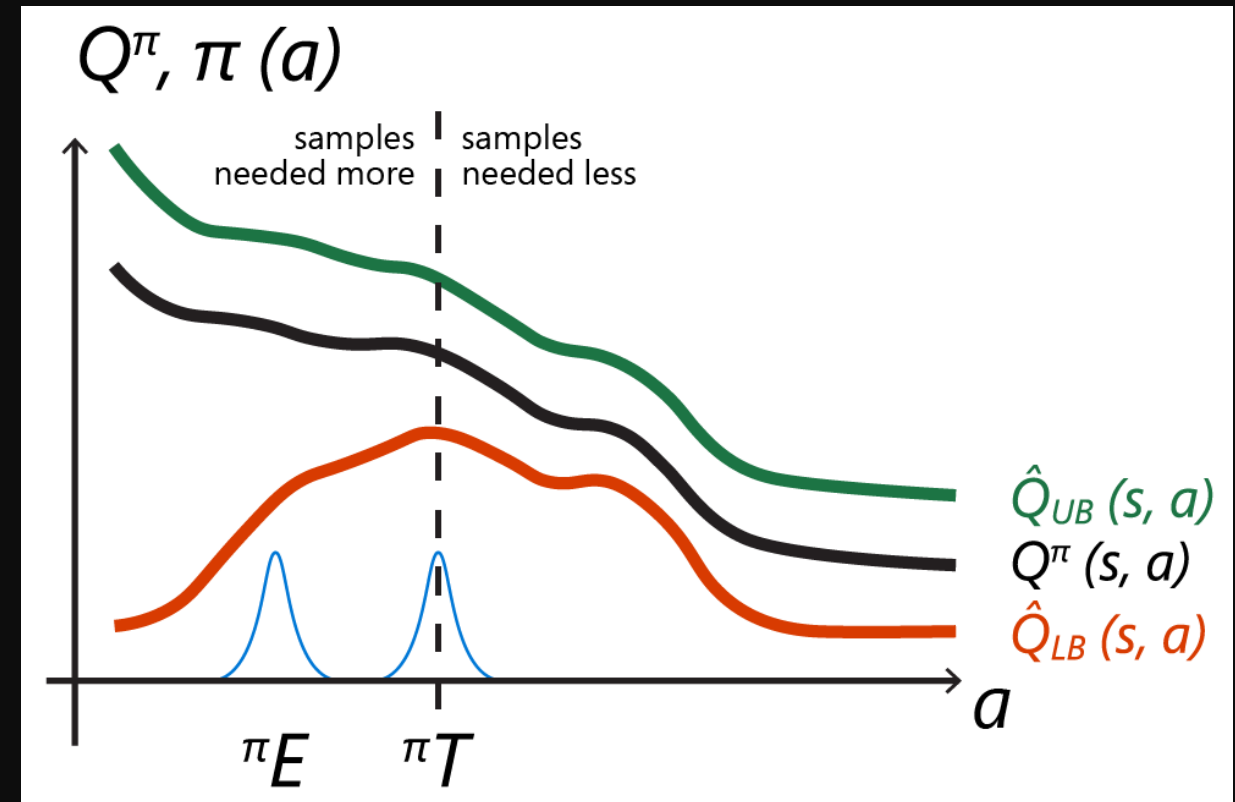
Focus on exploration in deep Actor Critic approaches

Insight: existing approaches tend to explore conservatively

Solution: more principled exploration using optimism

Upper confidence bound (optimistic estimate) on $\hat{Q}$:

$$\hat{Q}_{UB}(x, a) = \underbrace{\mu_Q(x, a)}_{\text{mean belief about } \hat{Q}} + \underbrace{\beta_{UB}\sigma_Q(x, a)}_{\text{uncertainty about } \hat{Q}}$$



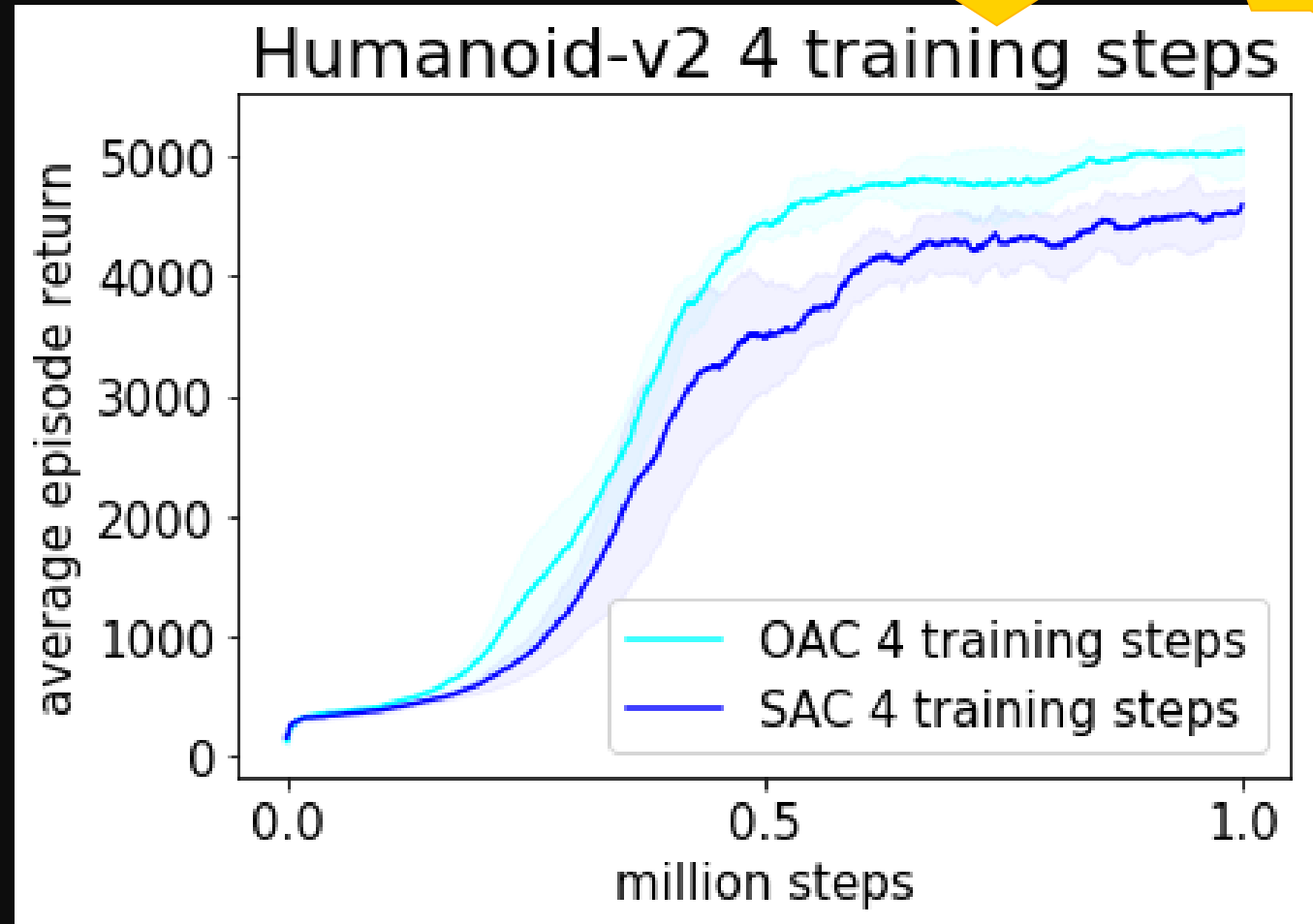
[Kamil Ciosek, Vuong, Loftin, Hofmann 2019]

Optimistic Actor Critic (OAC)

Key result: Optimistic exploration leads to efficient, stable learning in modern Actor Critic methods

Tue
spotlight
5:05PM
T3-S2

Tue
5:30PM
#179



[Kamil Ciosek, Vuong, Loftin, Hofmann 2019]

RL Applications

Example: Personalizer

Further study: ICML 2017 tutorial on Real World Interactive Learning by Alekh Agarwal and John Langford <http://hunch.net/~rwil/>

Example: Robotics

Further study: ICML 2017 tutorial on Deep Reinforcement Learning, Decision Making, and Control by Chelsea Finn and Sergey Levine <https://sites.google.com/view/icml17deeprl>

Example: Tutoring systems

Further study: NeurIPS 2017 tutorial on Reinforcement Learning for the People and/or by the People https://cs.stanford.edu/people/ebrun/NIPS_2017_tutorial_brunskill.pdf

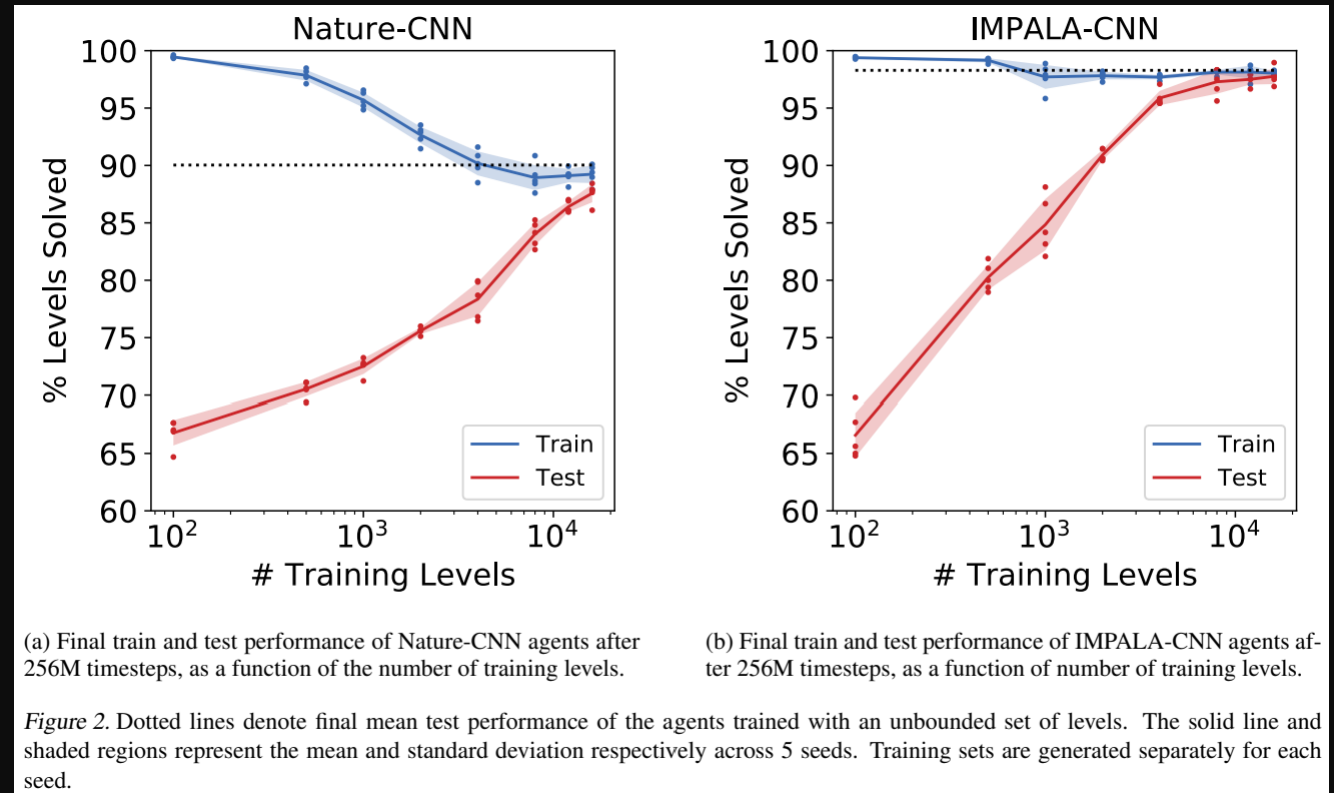
5. Generalization

Generalization in RL

Example: generalization using successor features [Dayan 1993], rapidly adapt to new reward structure [Barreto et al. 2018]

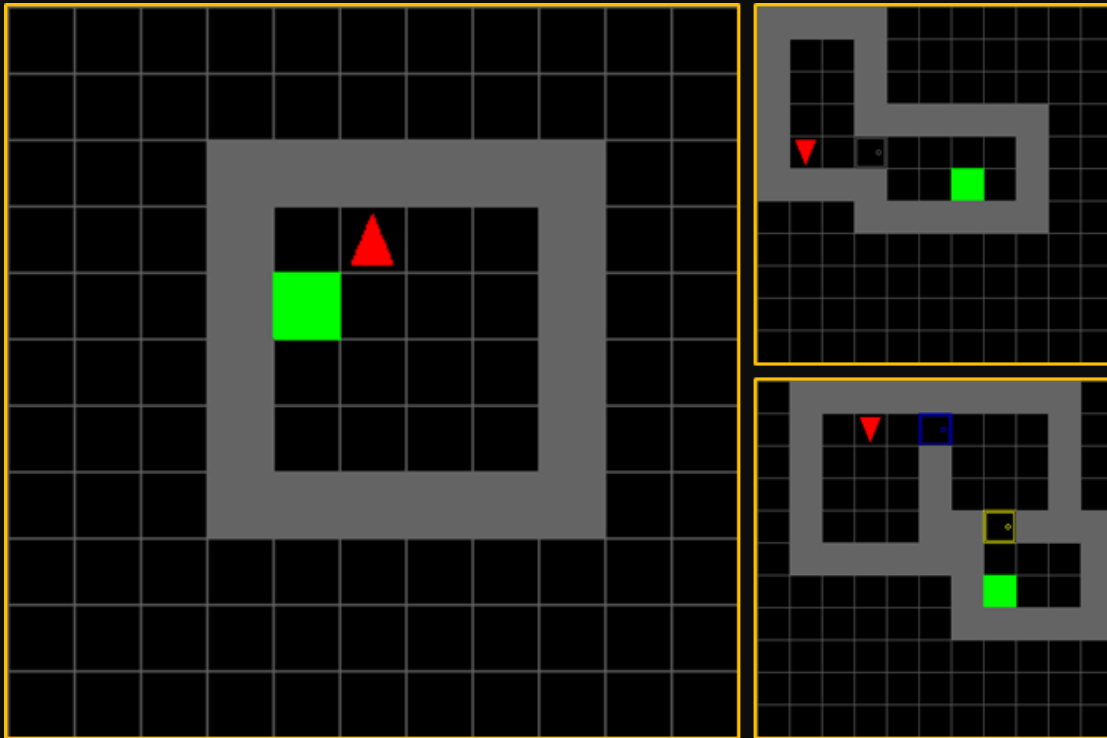
How many tasks are needed before modern approaches generalize?

[Cobbe et al. 2019]

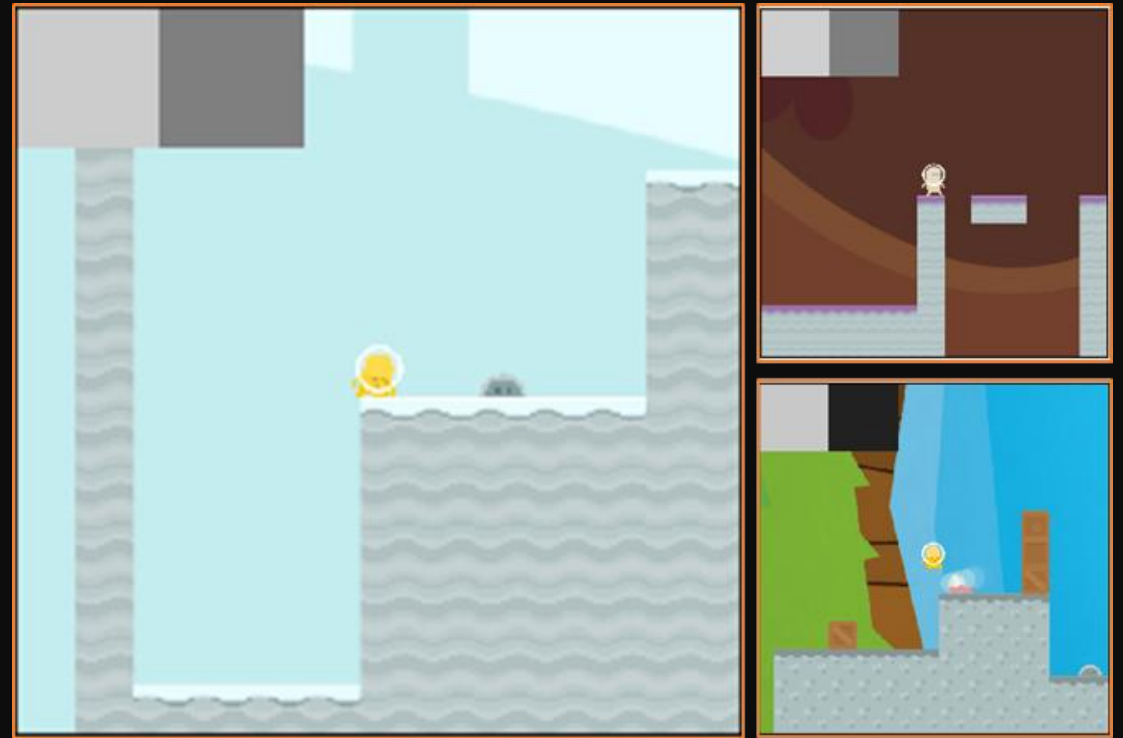


Generalization in RL

Recently proposed benchmarks:



Multi-Room
Chevalier-Boisvert et al. (2018)



CoinRun
Cobbe et al. (2019)

Generalization in Reinforcement Learning with Selective Noise Injection and Information Bottleneck

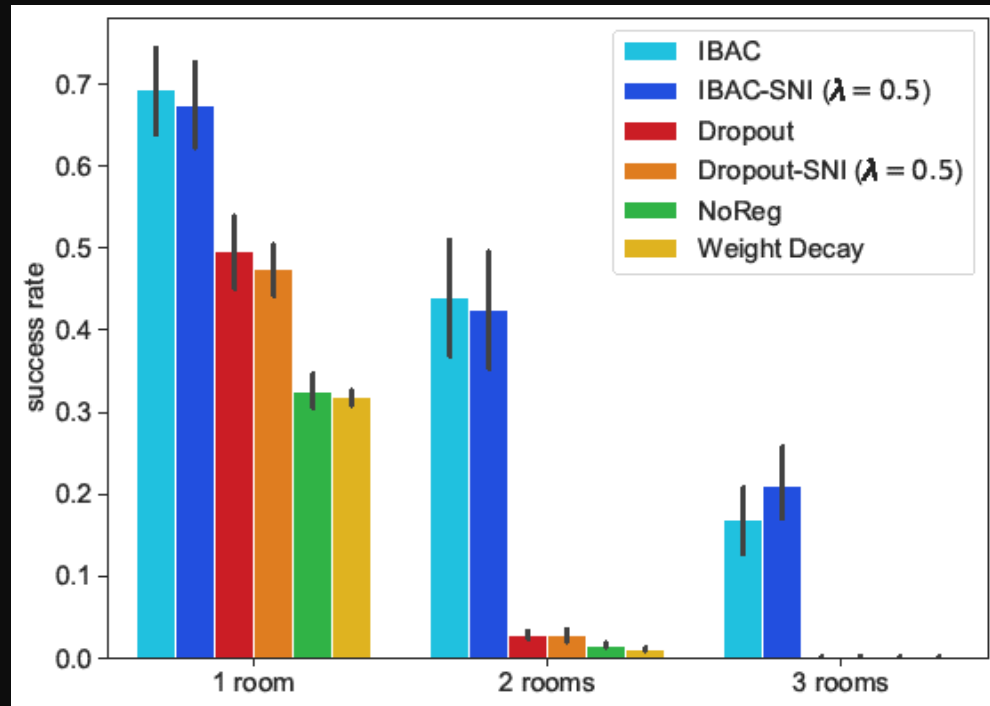
Previous regularization approaches developed for supervised learning, not RL!

Insight 1: Selective noise injection for **gradient update** but not **behavior (rollout) policy** speeds learning

Insight 2: regularization with Information bottleneck is particularly effective

$$\nabla_{\theta} J(\pi_{\theta}) = \hat{\mathbb{E}}_{\pi_{\theta}^r(a_t|x_t)} \left[\sum_t^T \frac{\pi_{\theta}(a_t|x_t)}{\pi_{\theta}^r(a_t|x_t)} \nabla_{\theta} \log \pi_{\theta}(a_t|x_t) \hat{A}_t \right]$$

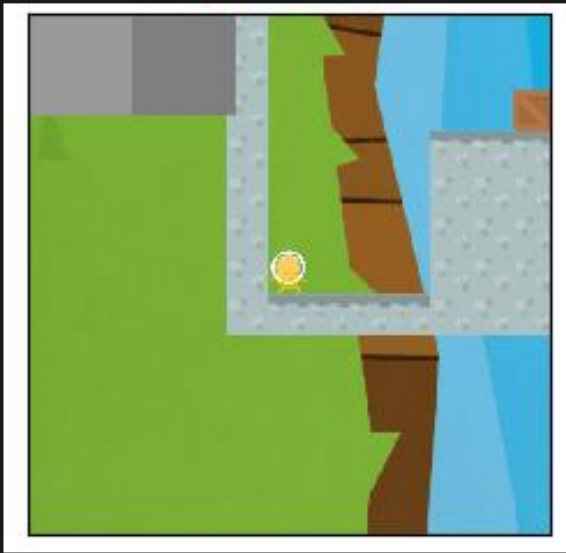
Generalization in Reinforcement Learning with Selective Noise Injection and Information Bottleneck



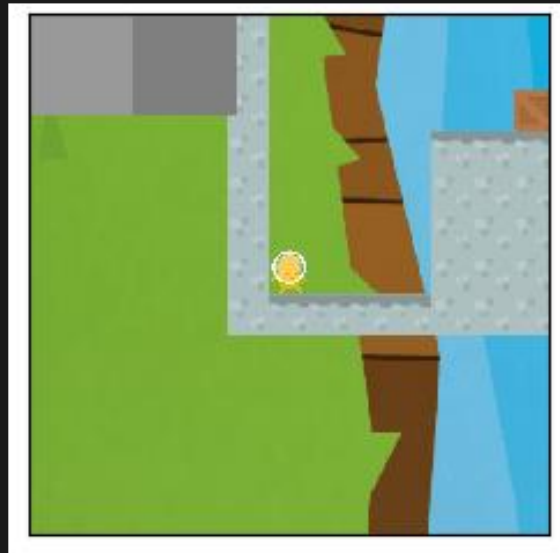
Key result: Dramatically improve performance on generalization benchmarks

Generalization in Reinforcement Learning with Selective Noise Injection and Information Bottleneck

Thu
10:45AM
#228



Baseline BatchNorm
regularizer



Our IBAC-SNI approach

Sat Dec 14th 8:00AM – 6:00PM
@ West 211 - 214

Learning Transferable Skills

Marwan Mattar · Arthur Juliani
Danny Lange · Matthew Crosby
Benjamin Beyret

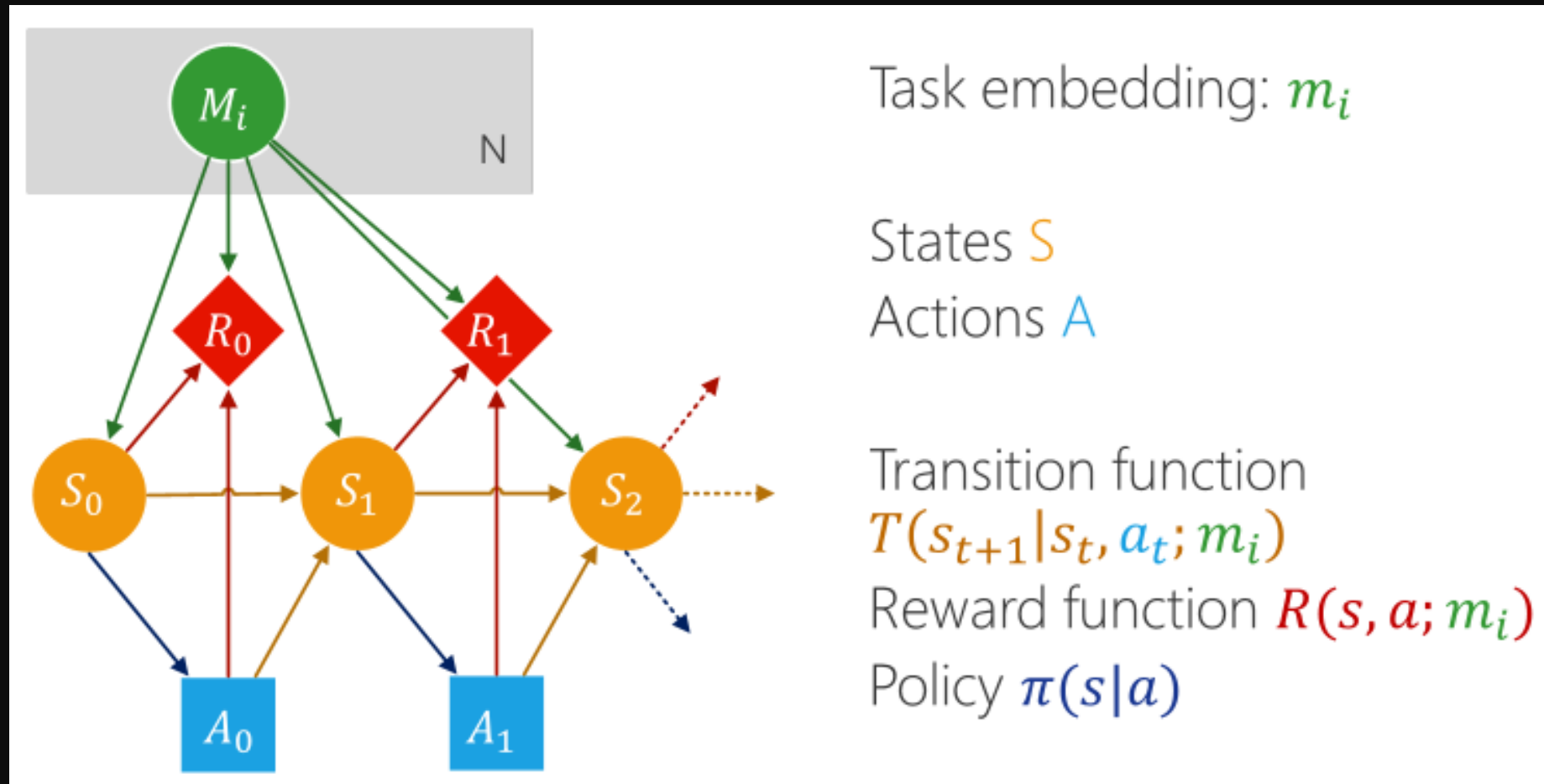
<https://www.skillsworkshop.ai/>

[Igl, Ciosek, Li, Tschitschek, Zhang, Devlin, Hofmann 2019]

6. Structure

Meta Learning

= Learn to Learn, e.g., learn an update rule from related tasks



Example, tasks are related through low-dimensional embedding

Model-Agnostic Meta Learning (MAML)

[Finn et al. 2017]

Flexible meta-learning approach based on 2nd order gradient descent

2-stage gradient-based approach on batches of tasks $\mathcal{T}$

1) Inner loop:

$$\theta'_i = \theta - \alpha \nabla_{\theta} \mathcal{L}_{\mathcal{T}_i}(f_{\theta})$$

2) Outer loop:

$$\theta = \theta - \beta \nabla_{\theta} \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}(f_{\theta'_i})$$

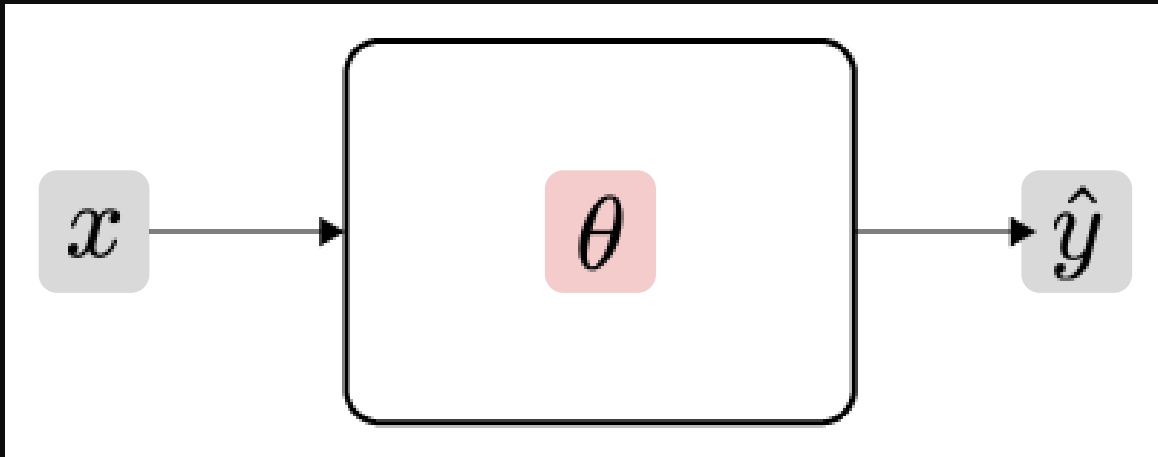
For more on Meta-Learning see ICML 2019 tutorial by Chelsea Finn and Sergey Levine
<https://sites.google.com/view/icml19metalearning>

Fast Context Adaptation via Meta-Learning (CAVIA)

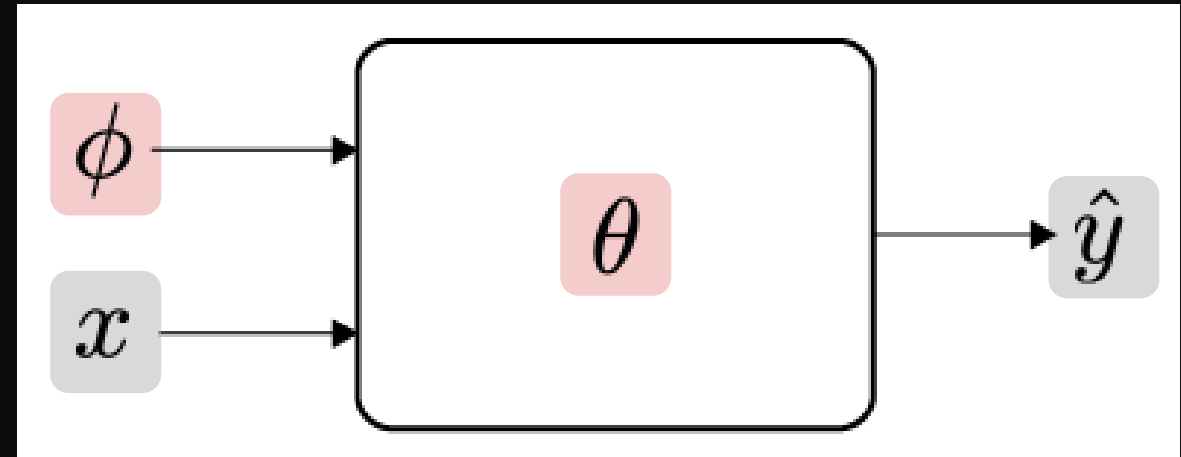
Problem: Many parameters + few data points can lead to overfitting

Key insight: Many tasks only require task identification – no need to update all model parameters at test time

MAML (Finn et al. 2017)

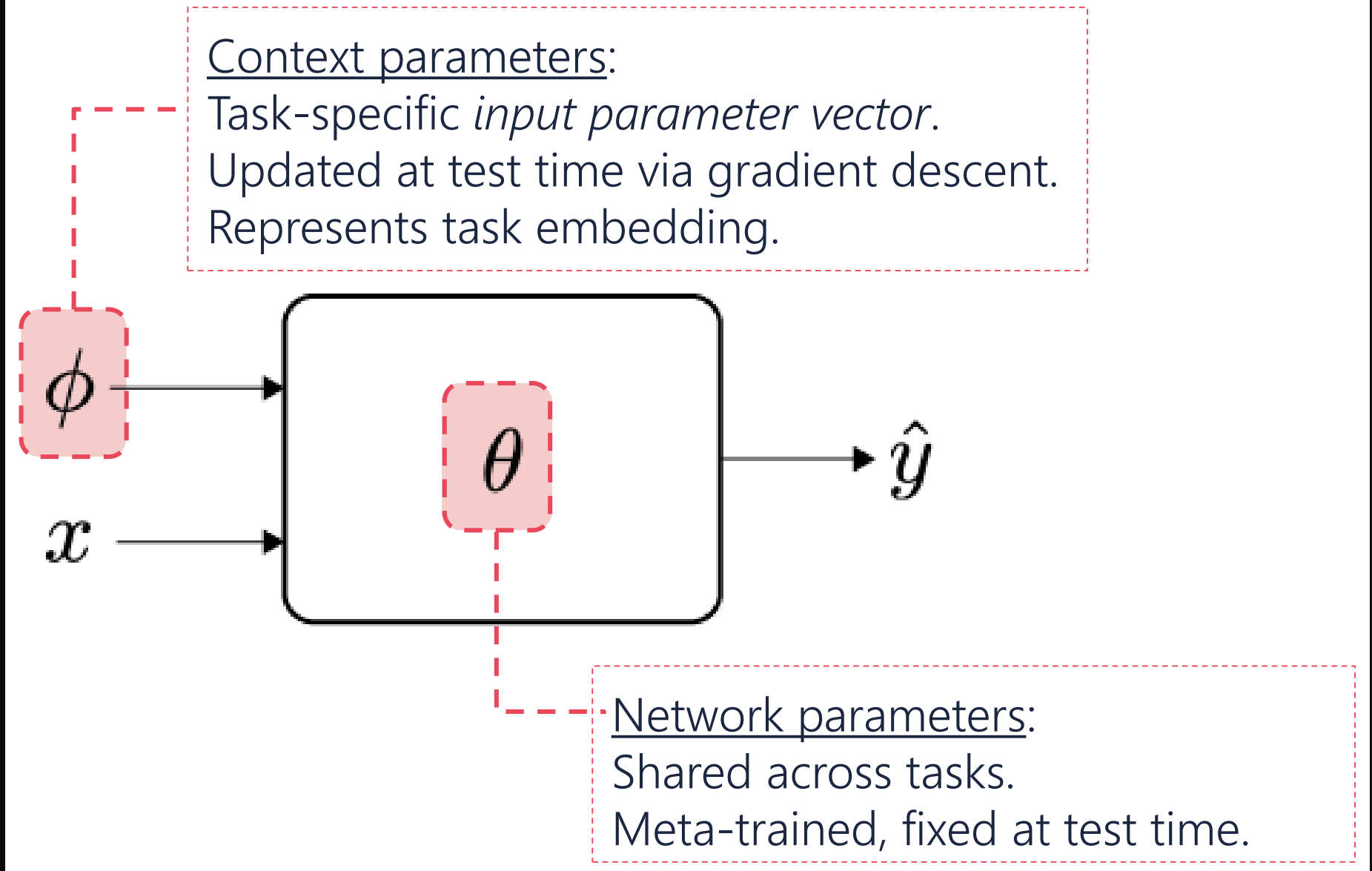


CAVIA



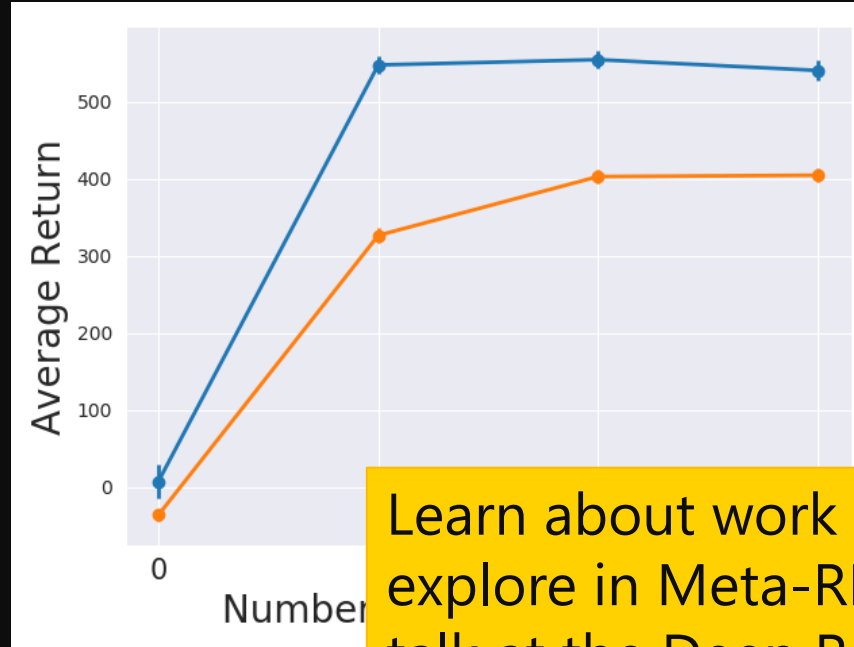
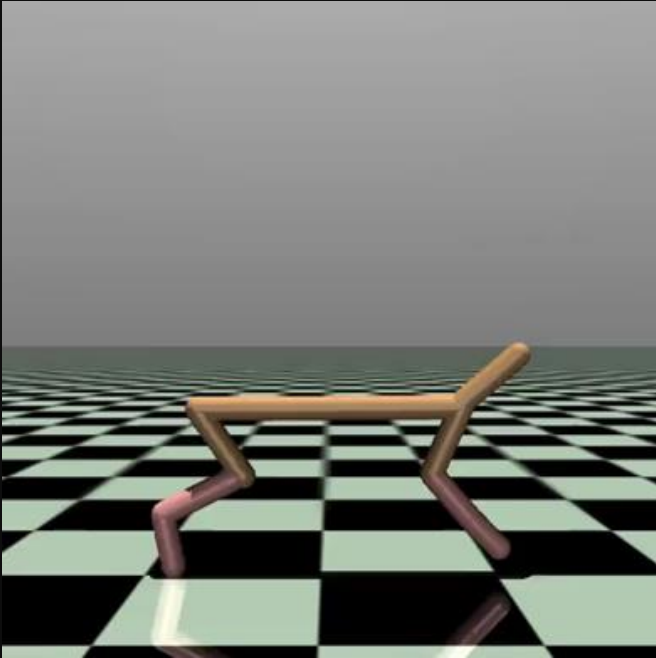
[Zintgraf, Shiarli, Kurin, Hofmann & Shimon Whiteson, 2019]

Overview



Fast Context Adaptation via Meta-Learning (CAVIA)

Results: Half-Cheetah directions task



CAVIA is less prone to overfitting

Learn about work in progress: learning to explore in Meta-RL settings – Shimon's invited talk at the Deep RL workshop on Sat, 10AM
<https://sites.google.com/view/deep-rl-workshop-neurips-2019/home>

[Zintgraf, Shiarli, Kurin, Hofmann & Shimon Whiteson, 2019]

7. Models

Model-based RL

Model: Dynamics: $T(s_{t+1}|s_t, a_t)$, Reward: $R(r_{t+1}|s_t, a_t)$

[Silver et al. 2016] – AlphaGo: Model is fully known

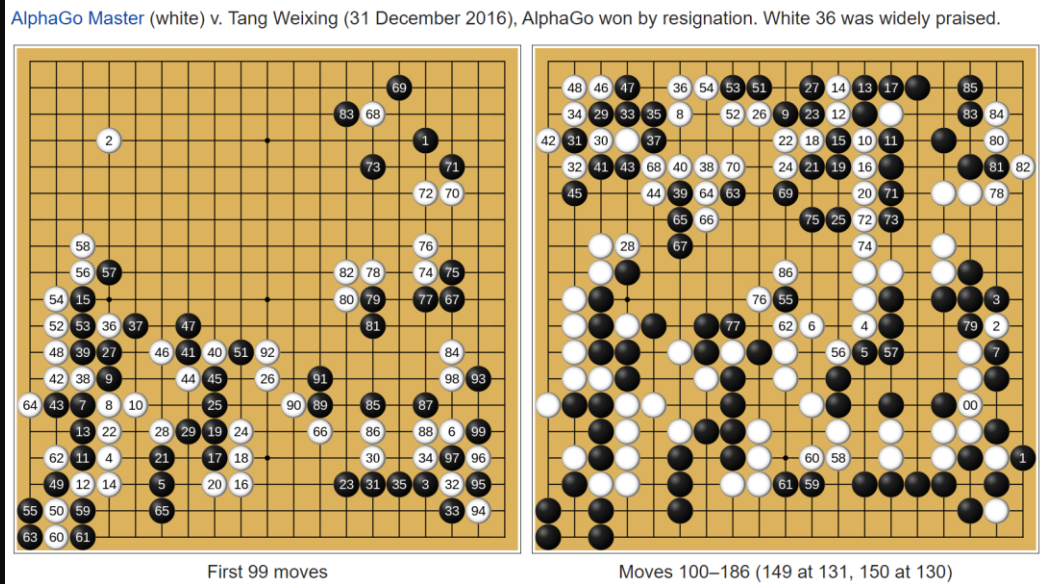
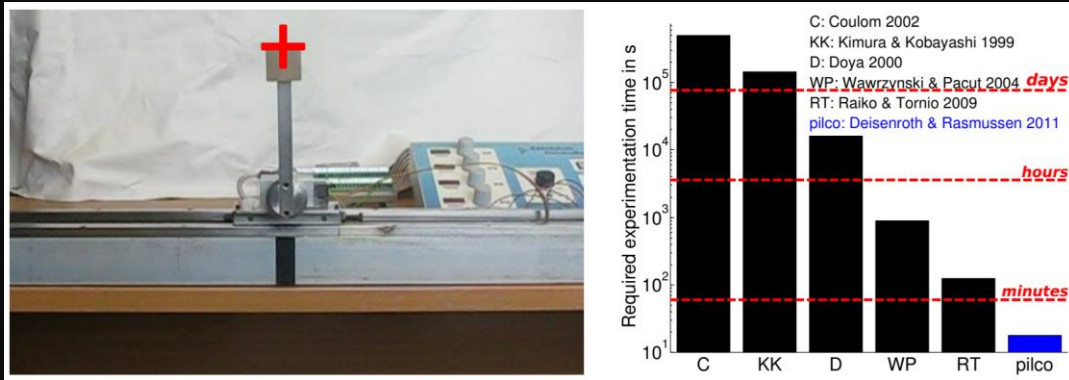


Image credit: <https://en.wikipedia.org/wiki/AlphaGo>

Model-based RL

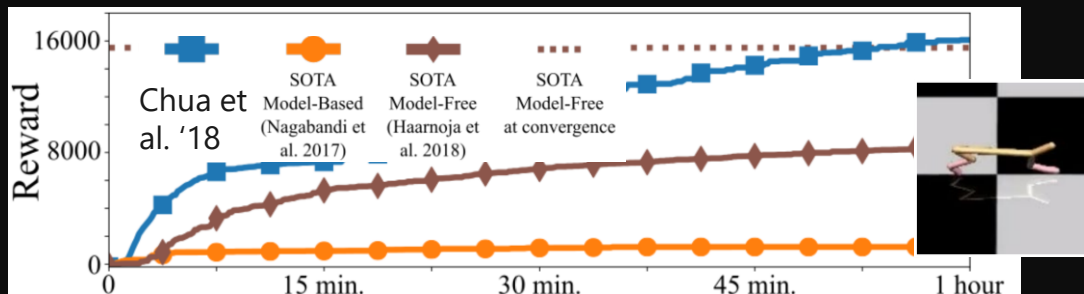
What if we don't know the model – learn from data?



[Deisenroth & Rasmussen 2011]
– PILCO – learns model
parameterized as Gaussian
Process



[Ha & Schmidhuber 2018] –
World Models – learn models
for policy optimization in visual
domains



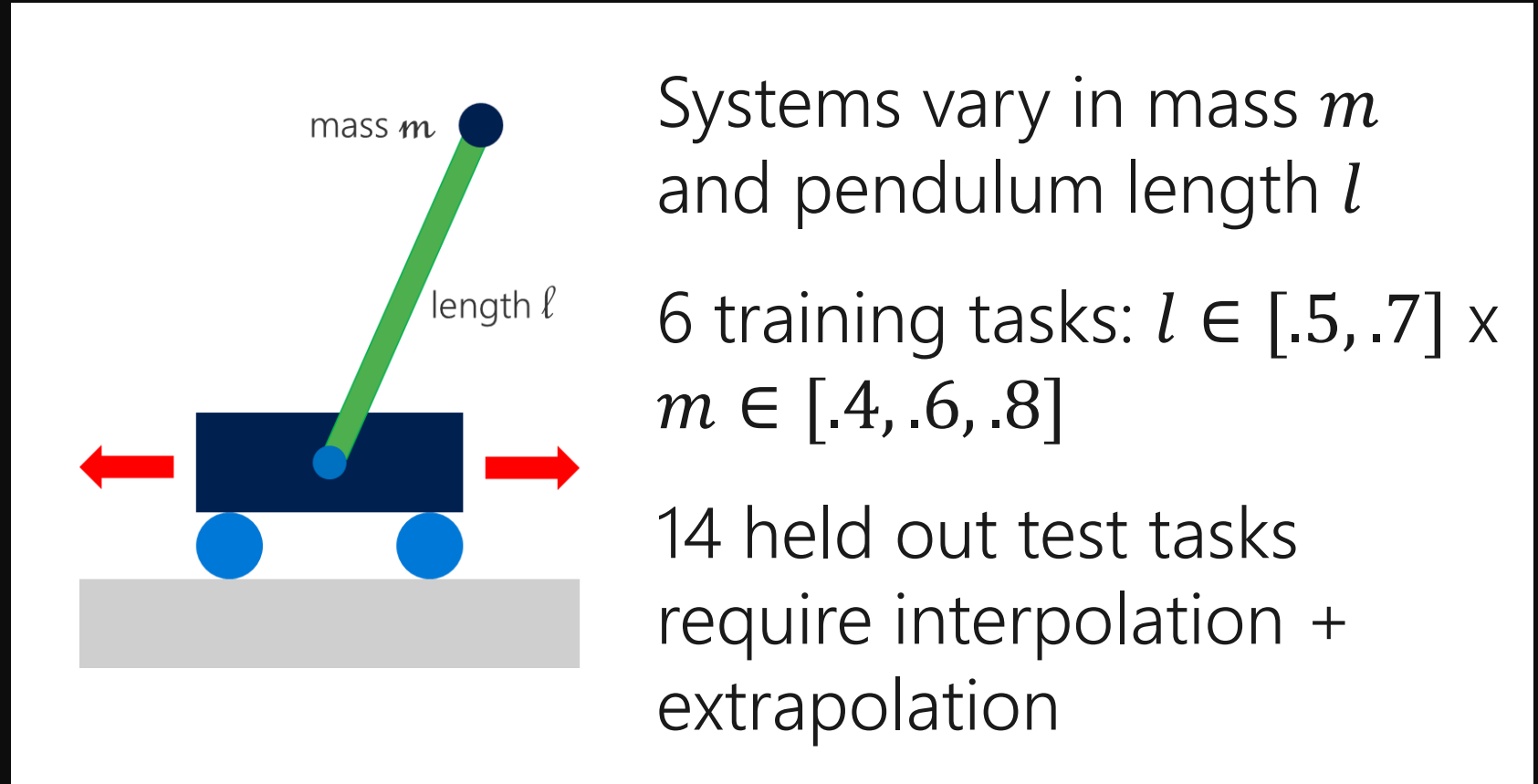
[Chua et al. 2018] – Learn
flexible models that quantify
uncertainty using ensembles of
Bayesian NNs

[Sun et al. 2019]
Identify settings
where model-
based RL provably
faster than model-
free approaches

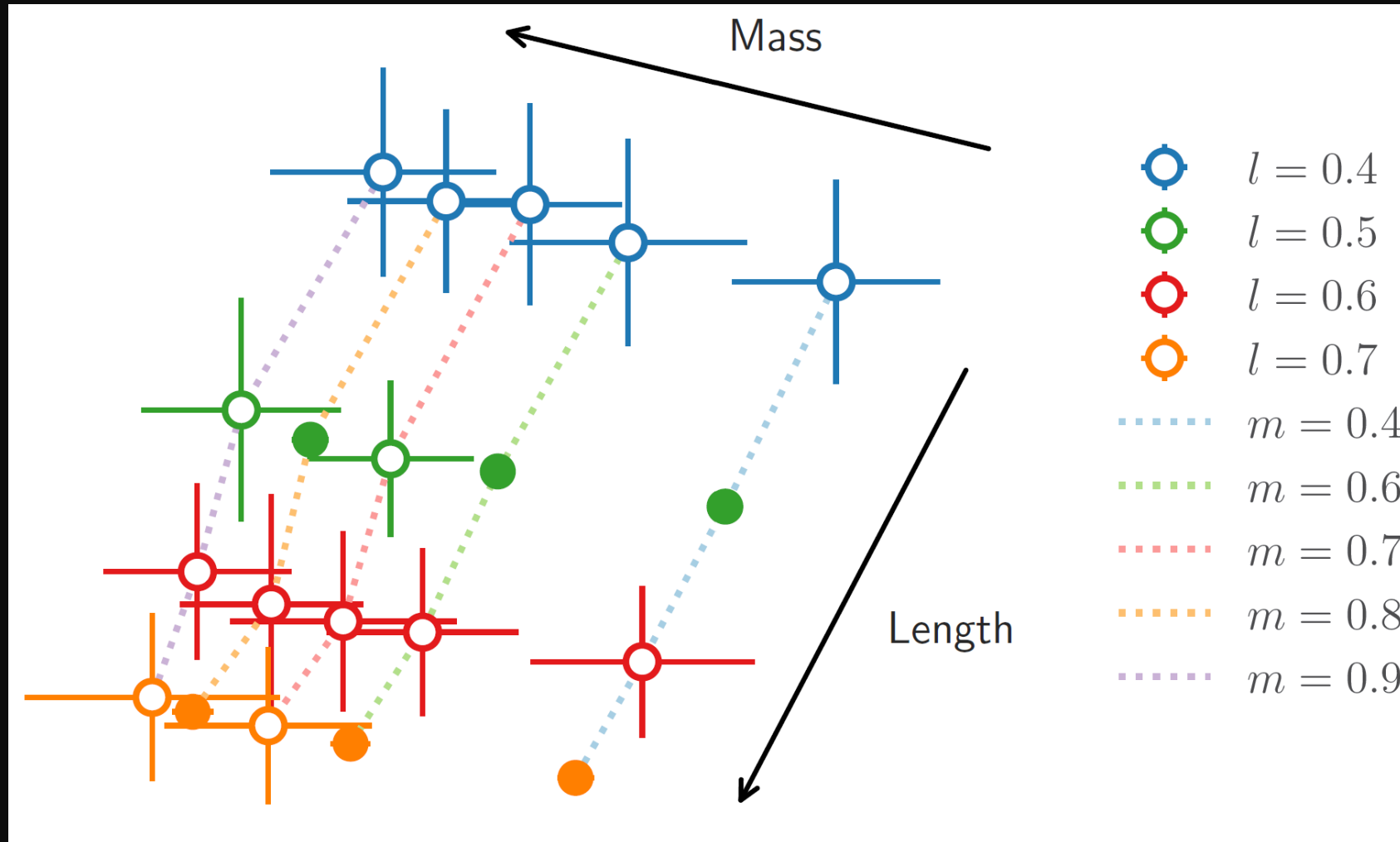
Meta-Learning for Model Identification

Goal: use data from related tasks to rapidly adapt model to new task

Approach: Gaussian Process dynamics conditioned on NN latent variable (optimized jointly)

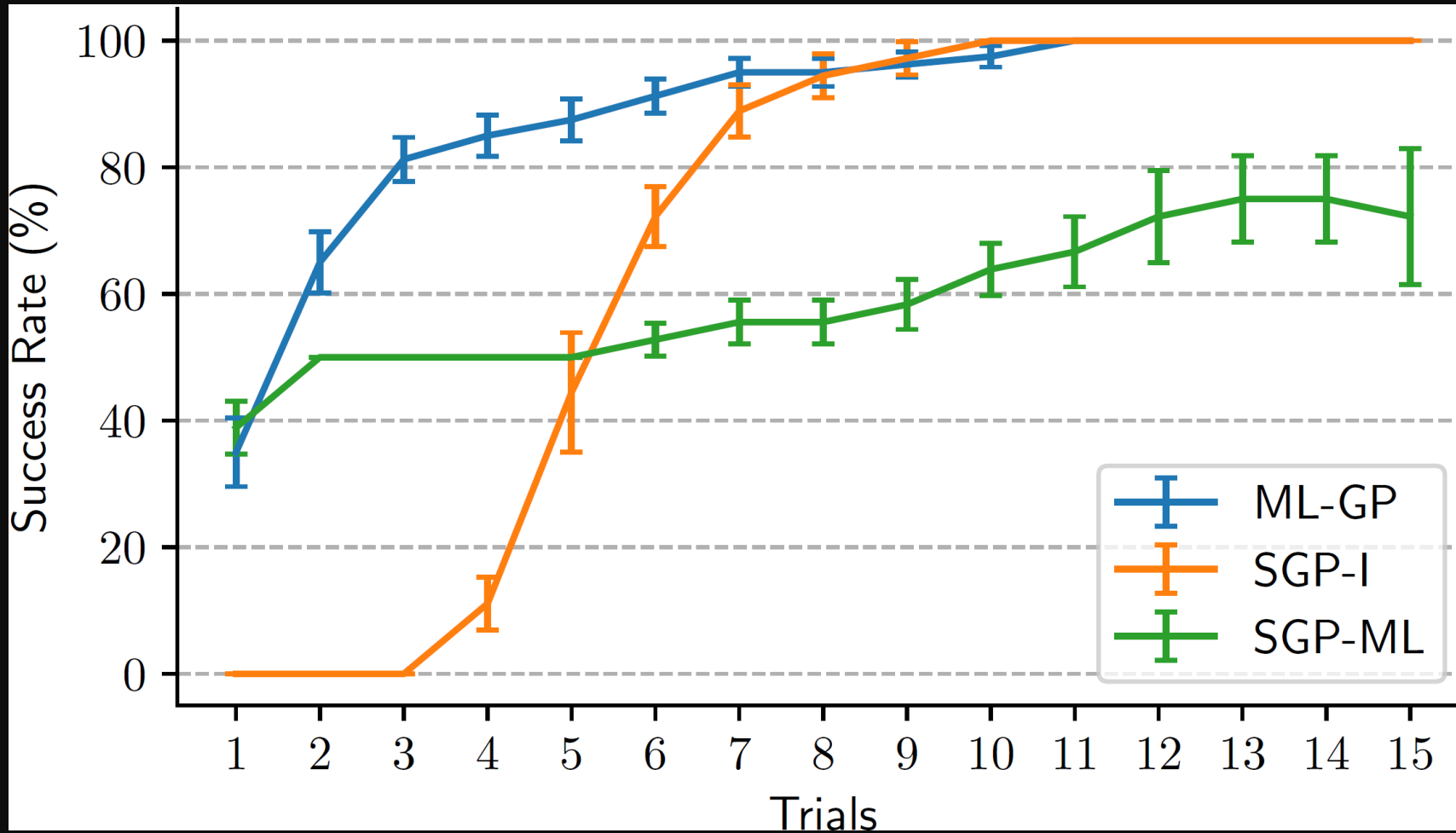


Multi-task Cart-Pole



Result 1: Learned embeddings accurately capture task structure

Multi-task Cart-Pole

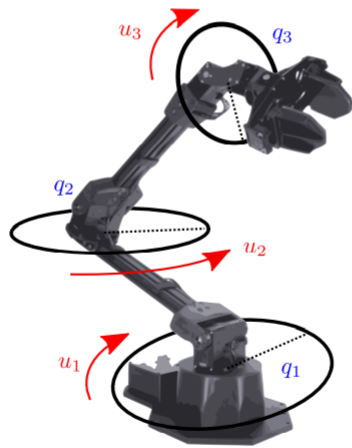


Result 2: dynamics model effectively uses multi-task structure for rapid adaptation

Using more (known) structure

Structural Priors

High-level prior knowledge: e.g., laws of physics or configuration constraints



Equations of motion

$$u = \frac{d}{dt} \left(\frac{\partial L}{\partial \dot{q}} \right) - \frac{\partial L}{\partial q}$$

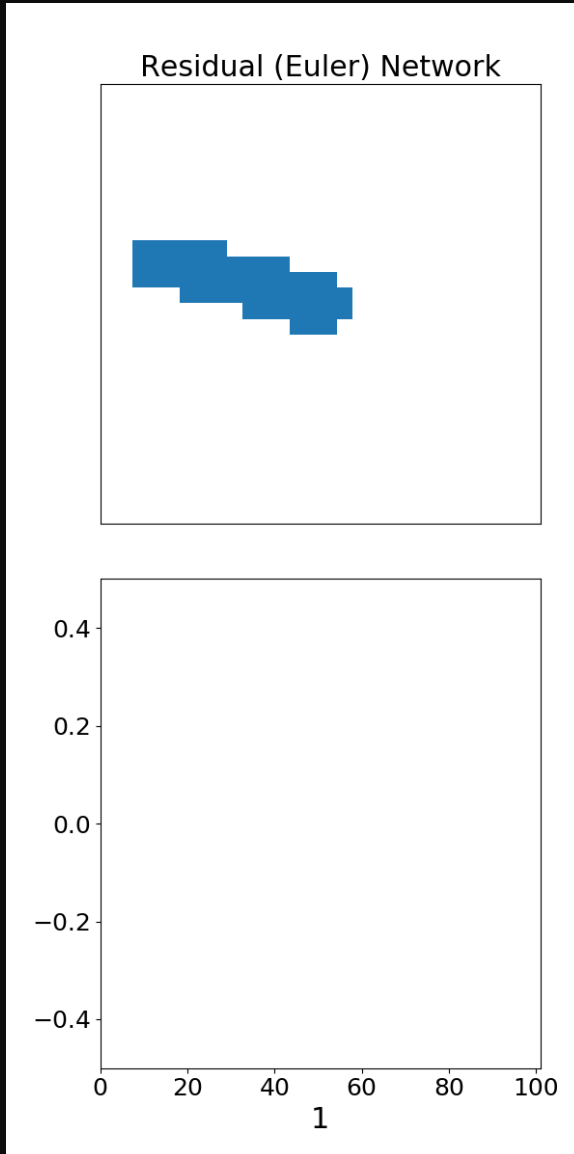
► Improve data efficiency and generalization

Image credit: Marc Deisenroth

Insight: propose Variational Integrator Networks (VINs) with built-in physics and geometric structure

[Sæmundsson, Terenin,
Hofmann & Deisenroth, 2019]

Using more (known) structure

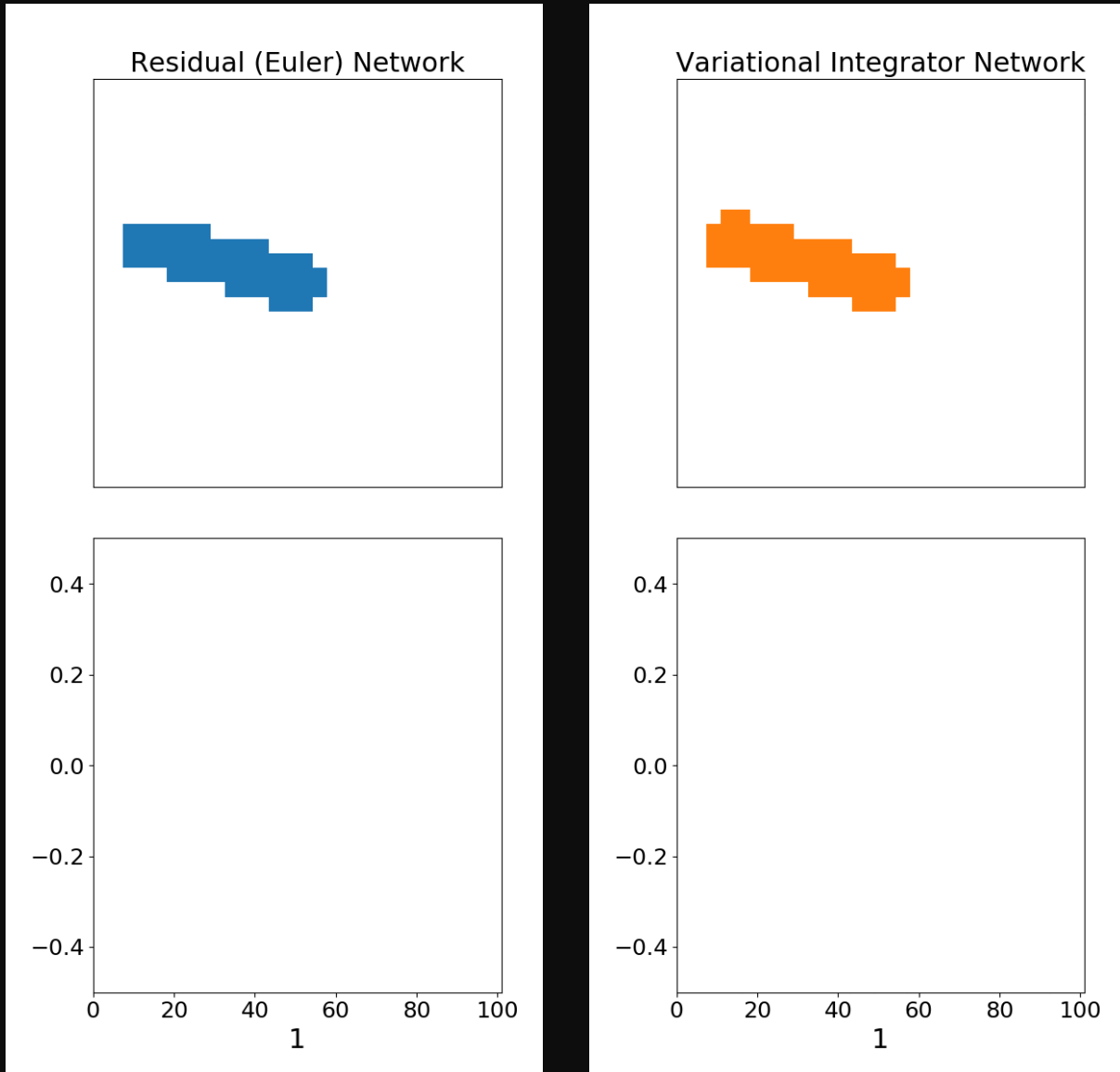


Result: VINs within auto-encoder setup effectively constrains latent space, learns from limited data.

Here: training on 40 images (28x28)

[Sæmundsson, Terenin, Hofmann & Deisenroth, 2019]

Using more (known) structure



Result: VINs within auto-encoder setup effectively constrains latent space, learns from limited data.

Here: training on 40 images (28x28)

For more details see Steindor's poster at the Bayesian Deep Learning workshop: Fri 9:35AM

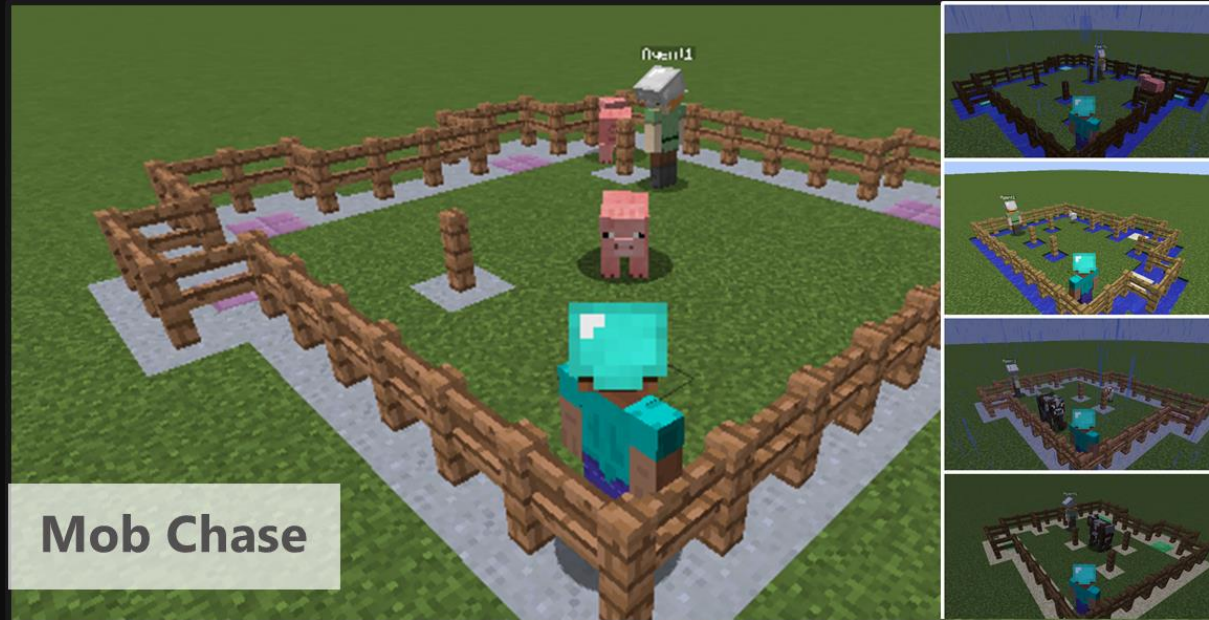
<http://bayesiandeeplearning.org/>

[Sæmundsson, Terenin, Hofmann & Deisenroth, 2019]

8. New Challenges

Multi-Agent Reinforcement Learning in Malmö (MARLO)

Agents collaborate to catch pig, chicken, or other mob in a small enclosure



One agent collects and carries treasure to a goal, the other defends the team from attackers



The Multi-Agent Reinforcement Learning in Malmö (MARLÖ)

Competition by Perez-Liebana et al.

<https://arxiv.org/abs/1901.08129>

Agents collaborate to build a structure, but the faster agent earns more rewards

The MineRL Competition on Sample Efficient Reinforcement Learning using Human Priors

NeurIPS 2019 Competition
Arxiv: 1904.10079

Organizing Team

William H. Guss (Carnegie Mellon University)
Mario Ynocente Castro (Preferred Networks)
Cayden Codel (Carnegie Mellon University)
Katja Hofmann (Microsoft Research)
Brandon Houghton (Carnegie Mellon University)
Noboru Kuno (Microsoft Research)
Crissman Loomis (Preferred Networks)
Keisuke Nakata (Preferred Networks)
Stephanie Milani (University of Maryland and CMU)
Sharada Mohanty (Alcrowd)
Diego Perez Liebana (Queen Mary University of London)
Ruslan Salakhutdinov (Carnegie Mellon University)
Shinya Shiroshita (Preferred Networks)
Nicholay Topin (Carnegie Mellon University)
Avinash Ummadisingu (Preferred Networks)
Manuela Veloso (Carnegie Mellon University)
Phillip Wang (Carnegie Mellon University)

Advisory committee

Chelsea Finn (Google Brain and UC Berkeley)
Sergey Levine (UC Berkeley)
Harm van Seijen (Microsoft Research)
Oriol Vinyals (Google DeepMind)

Click to play (in powerpoint)

Video link: <https://www.microsoft.com/en-us/research/video/minerl-competition-2019/>

MineRL @ NeurIPS 2019 Competition Track

Top Submissions

Mountain Submission #24036
Episode #1
Submitted by: rolanchen

Net Reward
r(t): 0.00
net: 0.00

Action Visualization:
place 0
craft 0
nearbyCraft 4
nearbySmelt 0
↑ attack

0:00 / 2:09

Camera Control
YAW
[10.00, -10.00]
PITCH

1x

CDS Submission #24188
Episode #7
Submitted by: tviskaron

Net Reward
r(t): 0.00
net: 0.00

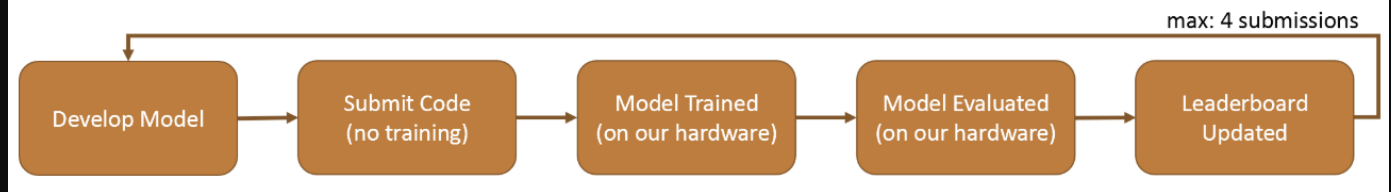
Action Visualization:
↑ attack

0:00 / 1:39

Camera Control
YAW
[0.00, -8.00]
PITCH

1x

ROUND 2: FINALS



Winners announced this Saturday
(Competition Track Day 2): 9AM

<http://minerl.io/competition/>

RL@NeurIPS





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References and Further Study:

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