Imagination and Curiosity

John Canny

Spring 2018

Lecture 22 of CS194/294-129: Designing, Visualizing and Understanding Deep Neural Networks

Some slides borrowed from S. Levine et al. "Deep Reinforcement Learning"

Last Time: Q Functions

$$\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) \underbrace{\left(\sum_{t'=1}^{T} \gamma^{t'-t} r(\mathbf{s}_{i,t'}, \mathbf{a}_{i,t'}) \right)}_{\text{"reward to go"}}$$

$\hat{Q}_{i,t}$

Define an expected value estimator Q:

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$$Q(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^{T} E_{\pi_\theta} \left[\gamma^{t'-t} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t \right] \quad : \text{true } \textit{expected} \text{ reward-to-go}$$

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$$\nabla_\theta J(\theta) \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t}|\mathbf{s}_{i,t}) Q(\mathbf{s}_{i,t},\mathbf{a}_{i,t})$$

Last Time: Advantage functions

$$Q(\mathbf{s}_t, \mathbf{a}_t) = \sum_{t'=t}^{T} E_{\pi_\theta}\left[\gamma^{t'-t} r(\mathbf{s}_{t'}, \mathbf{a}_{t'}) | \mathbf{s}_t, \mathbf{a}_t\right]$$

: true *expected* reward-to-go
total reward from taking $\mathbf{a}_t$ in $\mathbf{s}_t$

Value function $V^\pi(\mathbf{s}_t) = E_{\mathbf{a}_t \sim \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}[Q^\pi(\mathbf{s}_t, \mathbf{a}_t)]$: total reward from $\mathbf{s}_t$

Advantage function $A^\pi(\mathbf{s}_t, \mathbf{a}_t) = Q^\pi(\mathbf{s}_t, \mathbf{a}_t) - V^\pi(\mathbf{s}_t)$: how much better $\mathbf{a}_t$ is

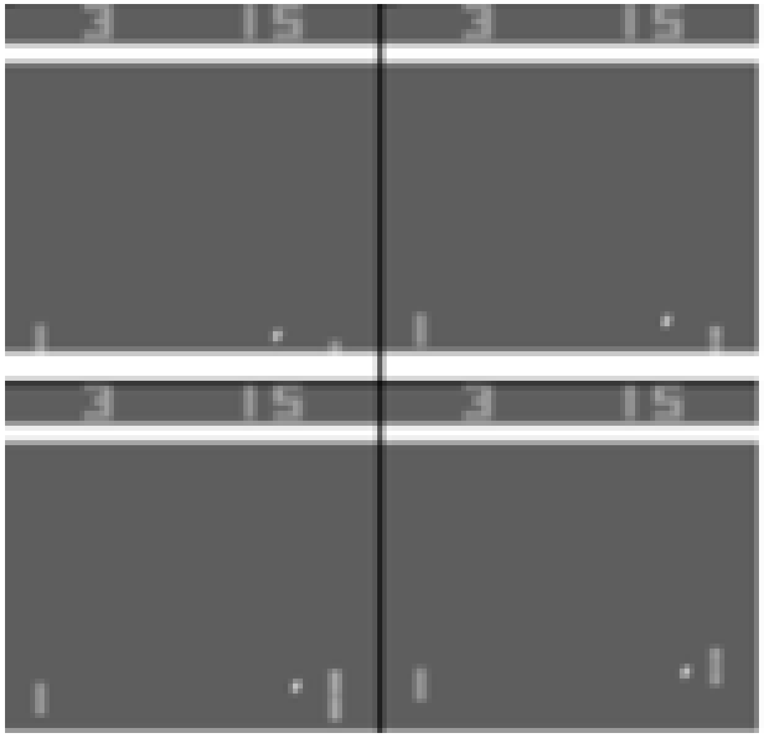
Advantage functions are typically ***sparse*** functions of state.

i.e. for many environments, most states have action advantages = 0.

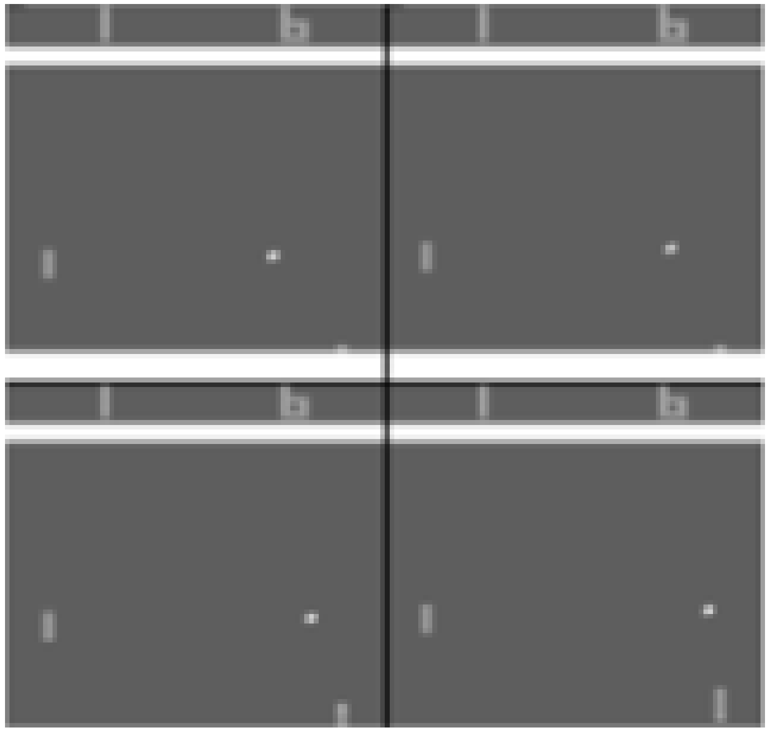
Advantage function Sparseness

Atari Pong, player on the right:

High advantage for some action:



Advantages close to zero
(action doesn’t affect reward)
true for most states:



Advantage functions address the ***temporal credit assignment problem***. Advantage focuses updates on actions that have high advantage, and ignores others:

Advantage function Sparseness

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Reinforce gradient: $\nabla_\theta J(\theta) \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_\theta \log \pi_\theta(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{t=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$

Actor-critic gradient: $\nabla_\theta J(\theta) \approx \sum_i \nabla_\theta \log \pi_\theta(\mathbf{a}_i | \mathbf{s}_i) \hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i)$

For the sequence $(s_0, a_0, s_1, a_1, s_2, a_2, s_3, a_3, s_4, a_4, s_5, a_5, \ldots)$
Advantages: 0, 0, 0, 1.2, 0, 0

Backpropagated gradient

Gradients only backpropagate to actions with non-zero advantage, i.e. only actions which affect the reward are reinforced.

Last Time: Actor-critic algorithms

batch actor-critic algorithm:

1. sample $\{\mathbf{s}_i, \mathbf{a}_i\}$ from $\pi_\theta(\mathbf{a}|\mathbf{s})$ (run it on the robot)
2. fit $\hat{V}^\pi_\phi(\mathbf{s})$ to sampled reward sums
3. evaluate $\hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i) = r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \hat{V}^\pi_\phi(\mathbf{s}'_i) - \hat{V}^\pi_\phi(\mathbf{s}_i)$
4. $\nabla_\theta J(\theta) \approx \sum_i \nabla_\theta \log \pi_\theta(\mathbf{a}_i|\mathbf{s}_i) \hat{A}^\pi(\mathbf{s}_i, \mathbf{a}_i)$
5. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

online actor-critic algorithm:

1. take action $\mathbf{a} \sim \pi_\theta(\mathbf{a}|\mathbf{s})$, get $(\mathbf{s}, \mathbf{a}, \mathbf{s}', r)$
2. update $\hat{V}^\pi_\phi$ using target $r + \gamma \hat{V}^\pi_\phi(\mathbf{s}')$
3. evaluate $\hat{A}^\pi(\mathbf{s}, \mathbf{a}) = r(\mathbf{s}, \mathbf{a}) + \gamma \hat{V}^\pi_\phi(\mathbf{s}') - \hat{V}^\pi_\phi(\mathbf{s})$
4. $\nabla_\theta J(\theta) \approx \nabla_\theta \log \pi_\theta(\mathbf{a}|\mathbf{s}) \hat{A}^\pi(\mathbf{s}, \mathbf{a})$
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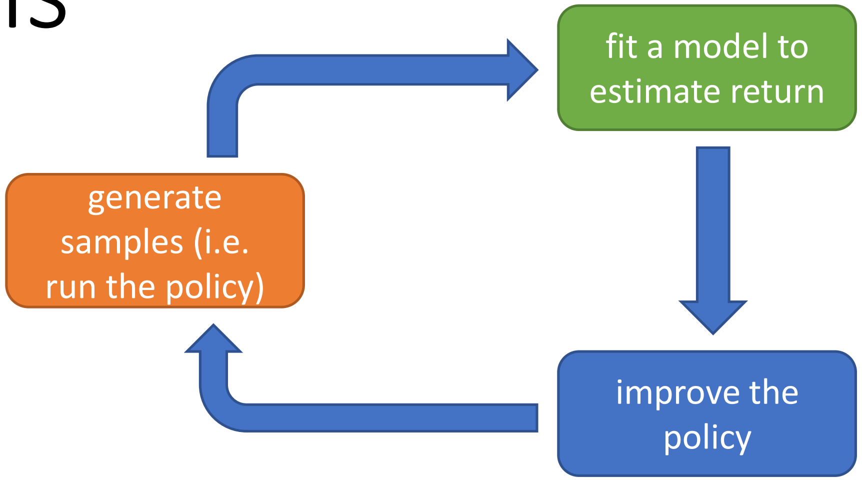
fit $\hat{V}^\pi$



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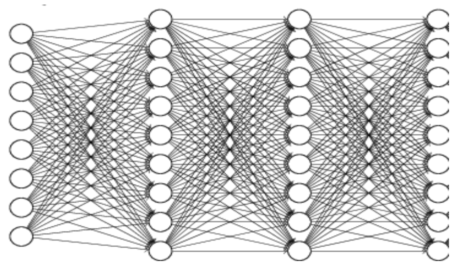
$\mathbf{s}$



$\hat{V}^\pi(\mathbf{s})$

parameters ϕ

Last Time: "Classic" deep Q-learning algorithm (DQN)

"classic" deep Q-learning algorithm:

1. take some action $\mathbf{a}_i$ and observe $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$, add it to $\mathcal{B}$
2. sample mini-batch $\{\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j, r_j\}$ from $\mathcal{B}$ uniformly
3. compute $y_j = r_j + \gamma \max_{\mathbf{a}'_j} Q_{\phi'}(\mathbf{s}'_j, \mathbf{a}'_j)$ using *target* network $Q_{\phi'}$
4. $\phi \leftarrow \phi - \alpha \sum_j \frac{dQ_\phi}{d\phi}(\mathbf{s}_j, \mathbf{a}_j)(Q_\phi(\mathbf{s}_j, \mathbf{a}_j) - y_j)$
5. update ϕ': copy ϕ every N steps

$$\left.\begin{array}{l}\text{2.}\\ \text{3.}\\ \text{4.}\end{array}\right\} K = 1$$

Mnih et al. '13

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Save to and sample from a replay buffer

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Use a target network, updated periodically

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Course Logistics

- Guest lectures next week by Chelsea Finn and Andrew Critch.

- Please try to attend in person.

- The course survey is on Wednesday, you can get that done as well...

Course Logistics

M 4/23	RL Capstone: Learning to Learn. **Chelsea Finn Guest Lecture.**		Assignment 4 due 11pm (pdf to Gradescope and zipfile to Bcourses)
W 4/25	Risks. **Andrew Critch Guest Lecture.**		
Su 4/29			Final Project Presentation due 11pm
M 4/30	Final project presentations I	4-5:30pm in 306 Soda Hall	Final Project Presentation
W 5/2	Final project presentations II	12:30-2:30pm in 306 Soda Hall	Final Project Presentation
Th 5/3	Final project poster session	3-4:30pm in Soda 5th floor atrium	Final Project Poster due
F 5/11			Final Project Report due

This Time: Curiosity and Imagination

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- Exploration vs. Exploitation

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- Exploration vs. Exploitation
- Exploration Methods:

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- Exploration Methods:
  - Optimistic exploration
  - Posterior sampling
  - Curiosity-driven exploration

- Model-free vs. model-based methods
  - Visual prediction
  - An imagination architecture

What’s the problem?

What's the problem?

this is easy (mostly)

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this is impossible

What's the problem?

this is easy (mostly)

Why?

this is impossible

Montezuma’s revenge

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- Getting key = reward

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Montezuma's revenge

- Getting key = reward
- Opening door = reward
- Getting killed by skull = nothing (is it good? bad?)
- Finishing the game only weakly correlates with rewarding events
- We know what to do because we **understand** what these sprites mean!

Exploration and exploitation examples

Examples from D. Silver lecture notes: http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching_files/XX.pdf

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- Online ad placement
  - Exploitation: show the most successful advertisement

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- Thompson sampling style algorithms:
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  - sample and act according to sample
- Information gain style algorithms
  - reason about information gain from visiting new states

Optimistic exploration in RL

UCB (Upper Confidence Bound) methods for MDPs

Define $N(s)$ as the number of times we have visited state s,
or $N(s,a)$ as the number of times we performed action a in state s.

Add an intrinsic reward of bonus for visiting rarely-visited states:

use $r^+(\mathbf{s},\mathbf{a}) = r(\mathbf{s},\mathbf{a}) + \mathcal{B}(N(\mathbf{s}))$

bonus that decreases with $N(\mathbf{s})$, e.g. $\mathcal{B}\big(N(s)\big) = \sqrt{\frac{2 \ln T}{N(s)}}$

use $r^+(\mathbf{s},\mathbf{a})$ instead of $r(\mathbf{s},\mathbf{a})$ with any model-free algorithm

+ simple addition to any RL algorithm

- need to tune bonus weight

The trouble with counts

use $r^+(\mathbf{s}, \mathbf{a}) = r(\mathbf{s}, \mathbf{a}) + \mathcal{B}(N(\mathbf{s}))$

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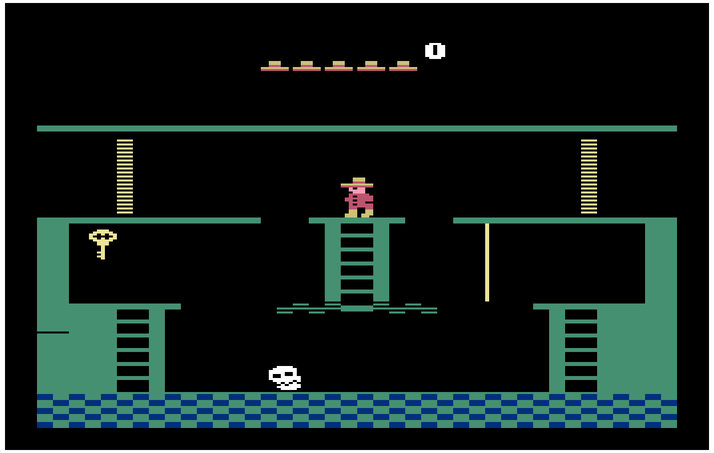

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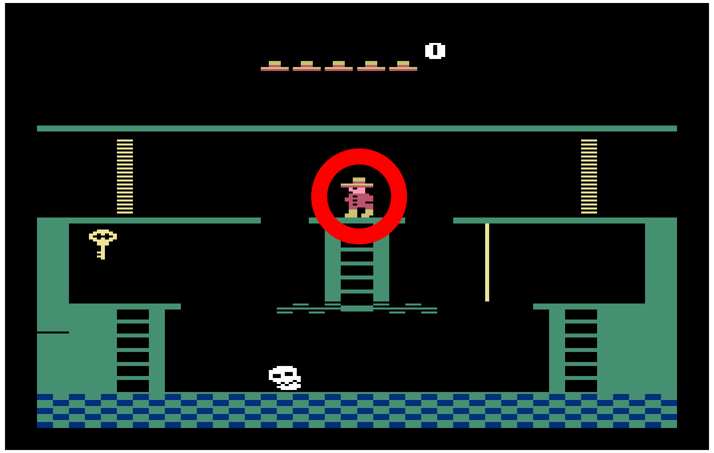

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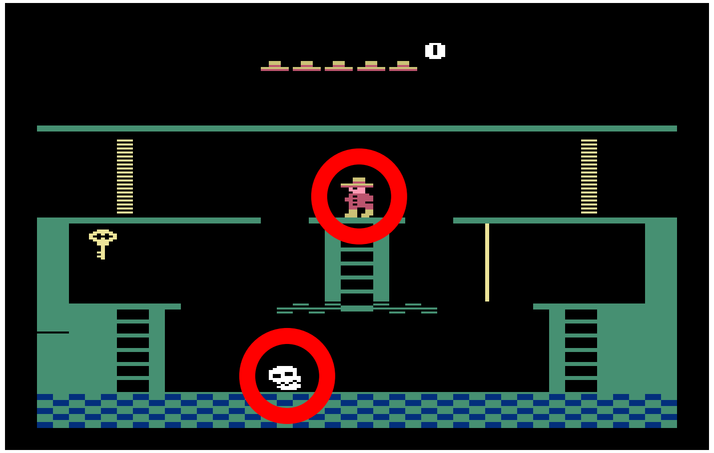

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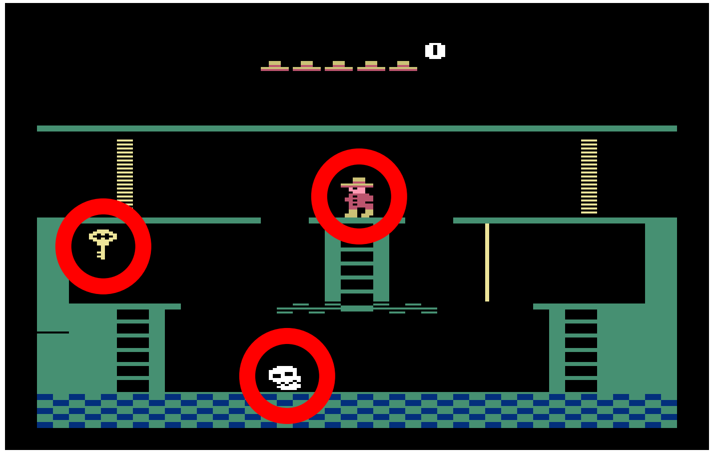

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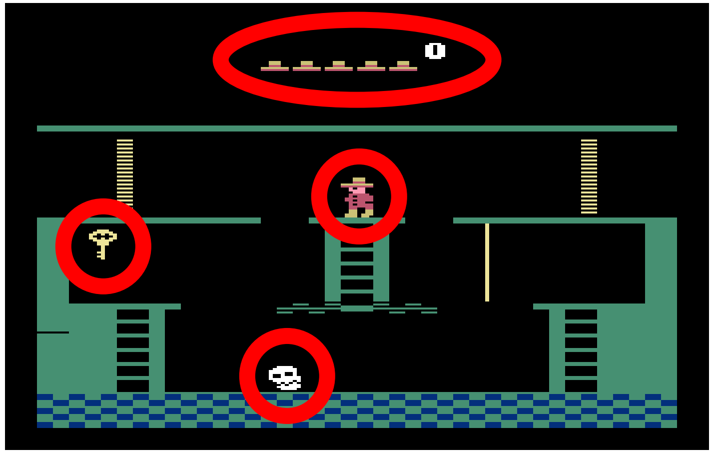

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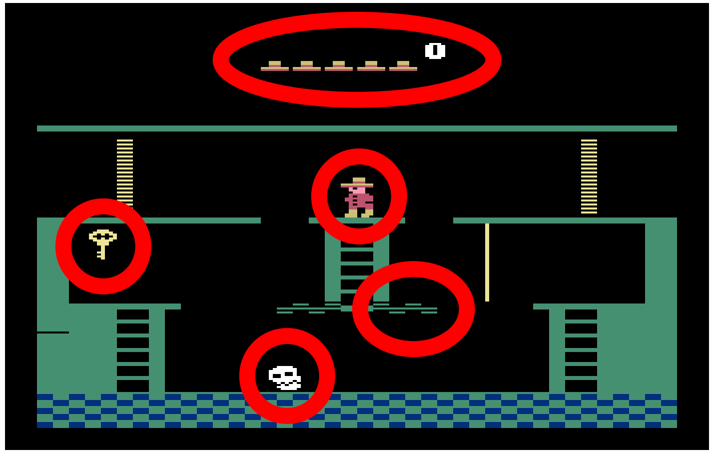

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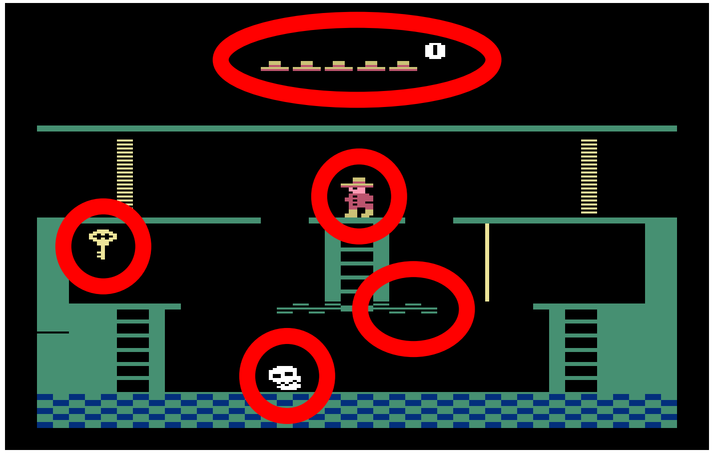

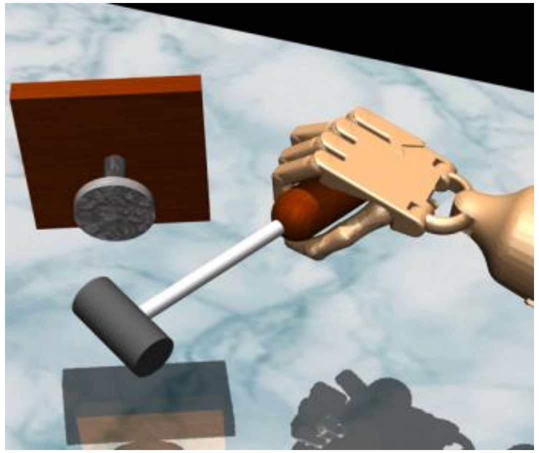

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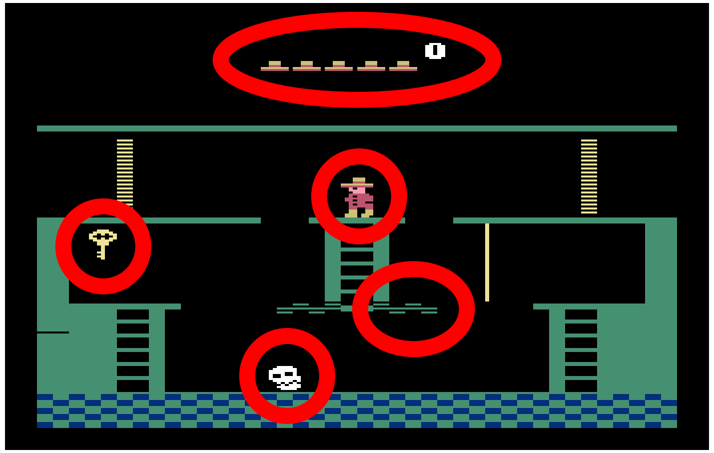

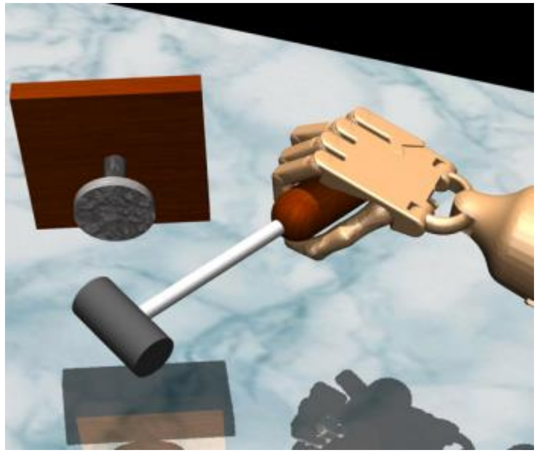

Uh oh… we never see the same thing twice!

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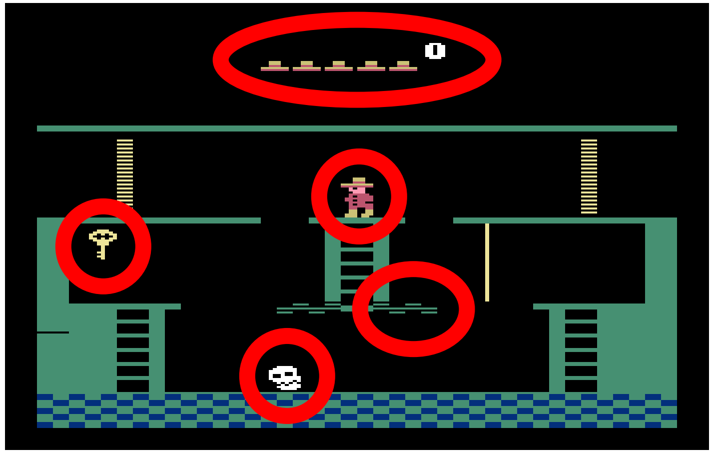
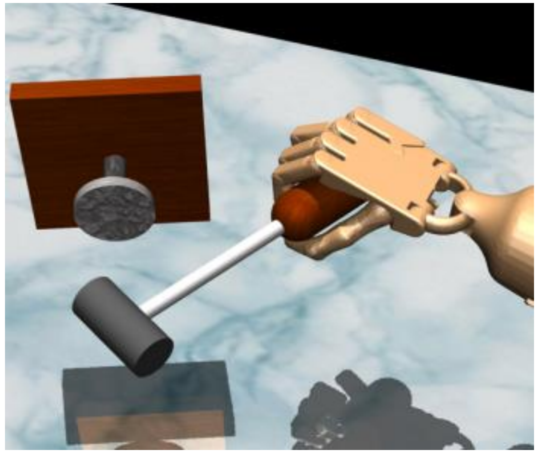
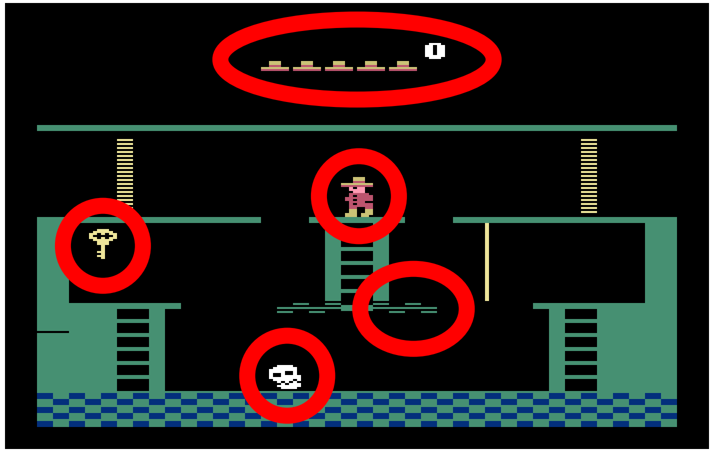


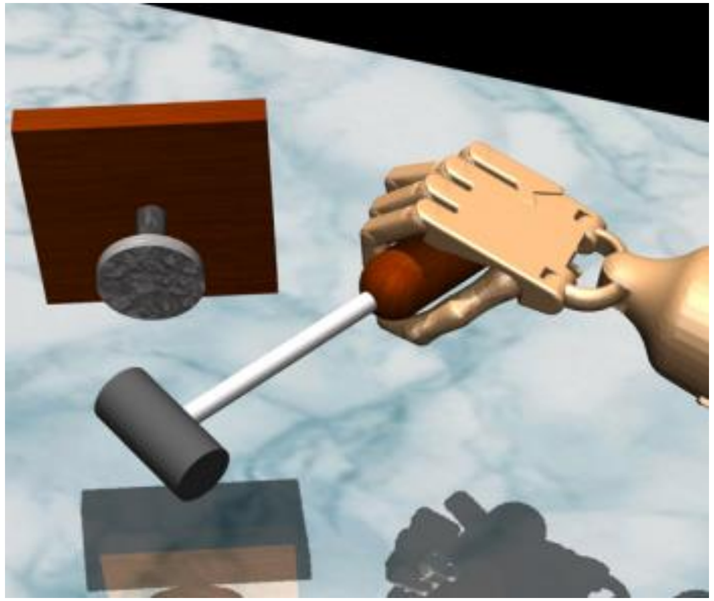


Uh oh… we never see the same thing twice!

But some states are more similar than others

Fitting generative models





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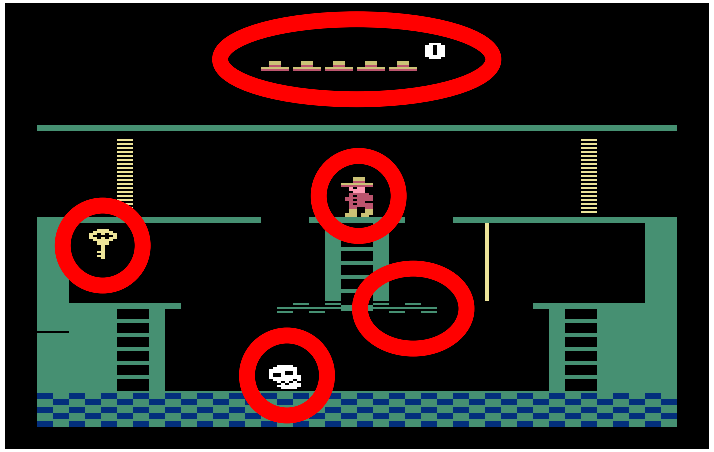

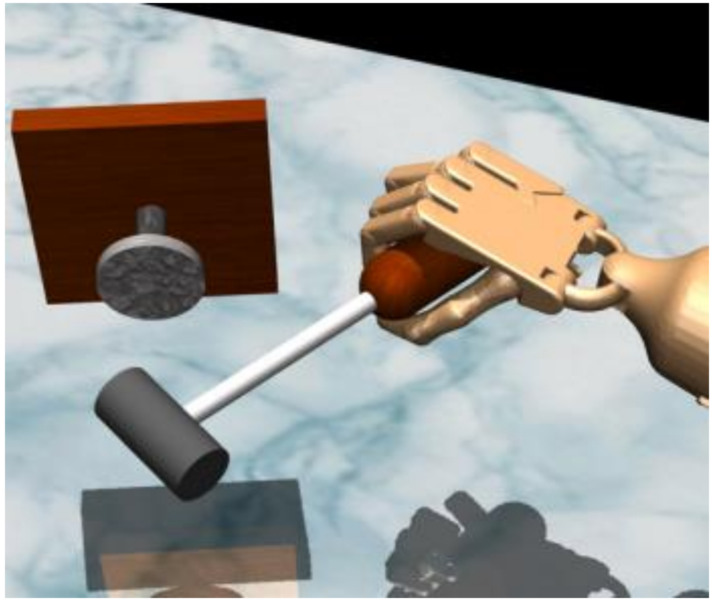

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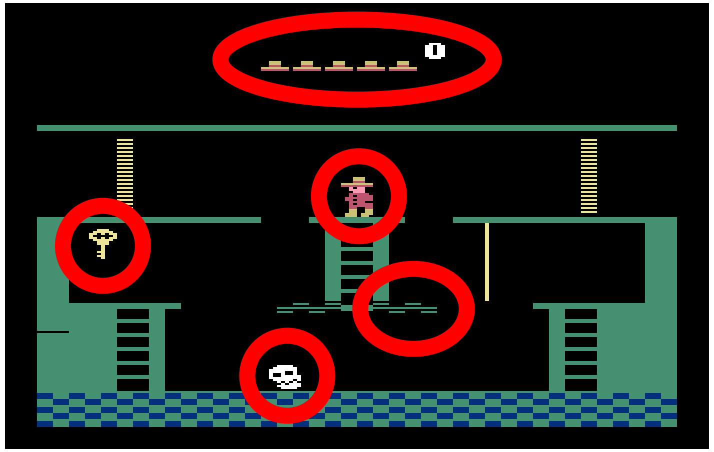

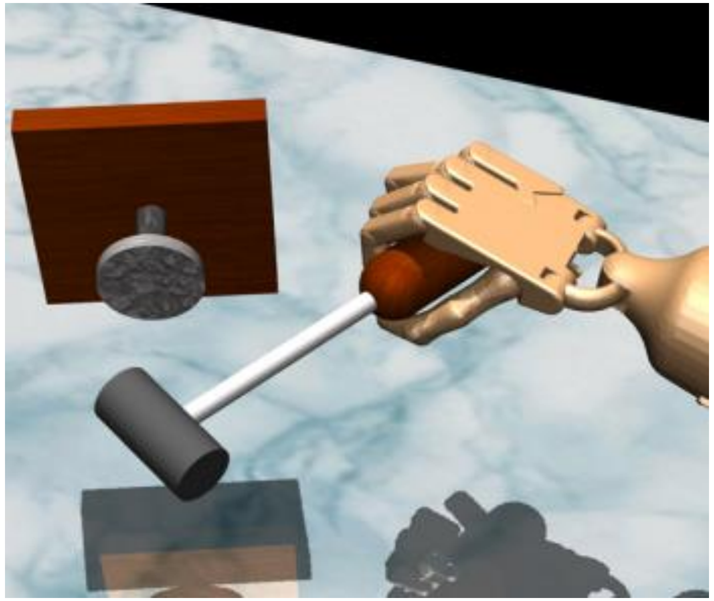

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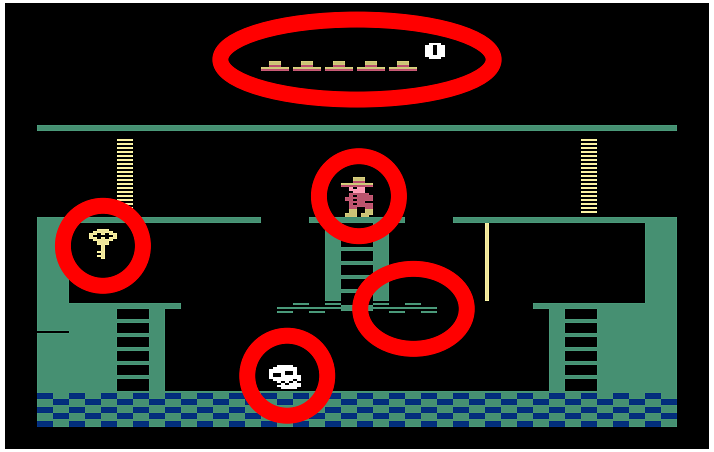

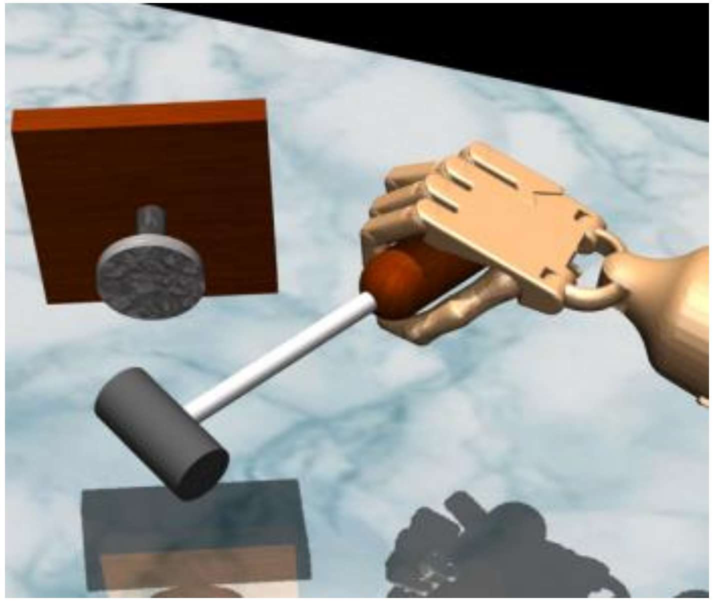

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if we have small MDPs
the true probability is:

$$P(\mathbf{s}) = \frac{N(\mathbf{s})}{n}$$

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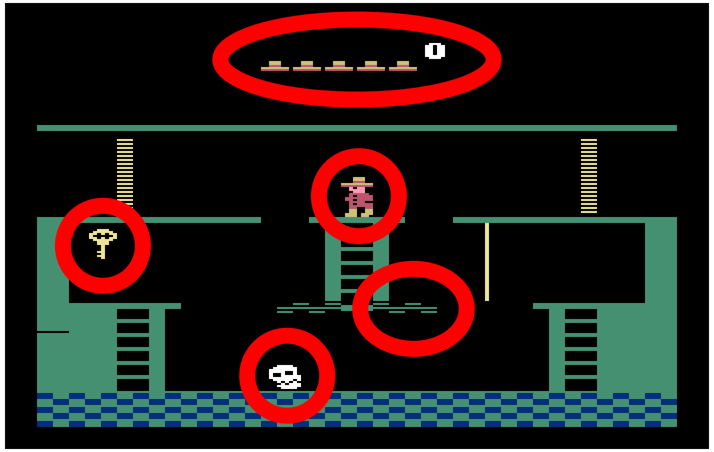

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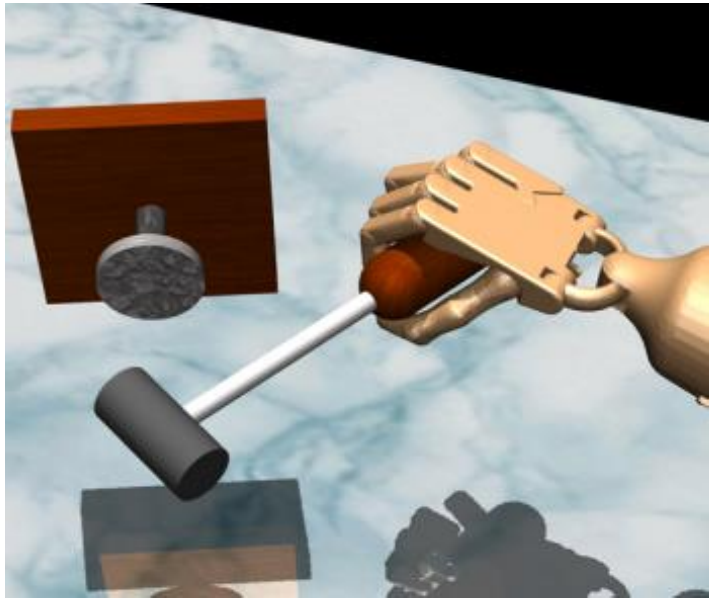

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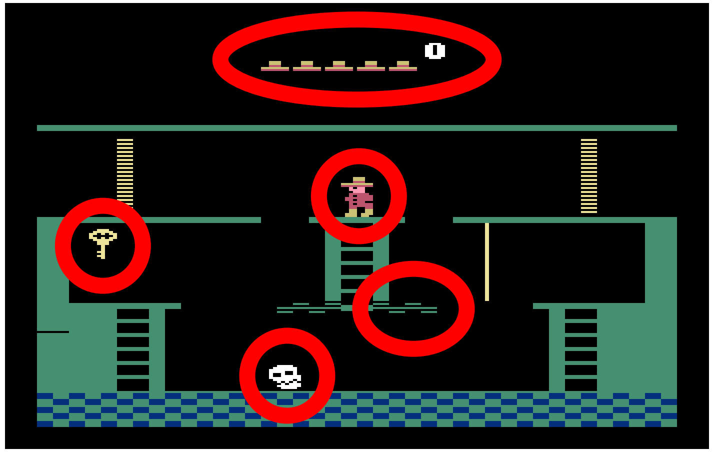
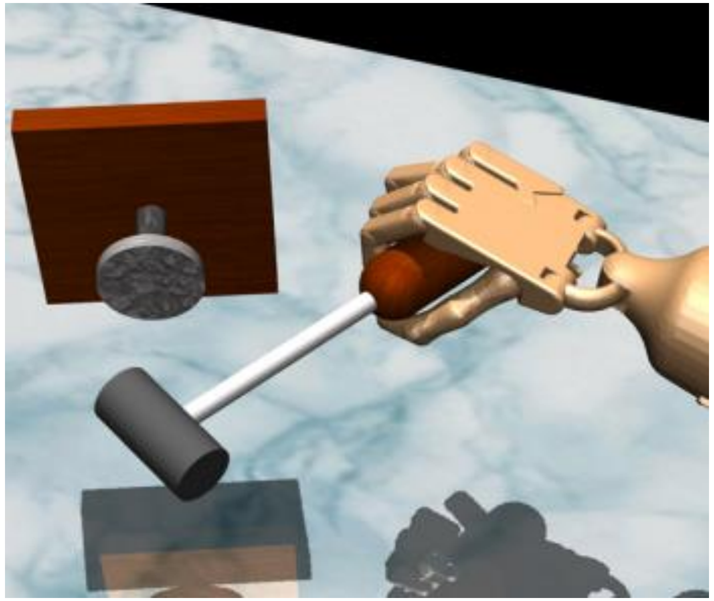
probability/density

Fitting generative models





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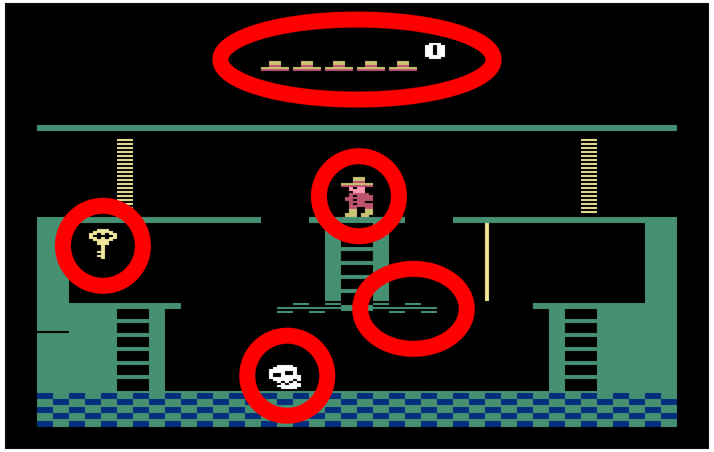

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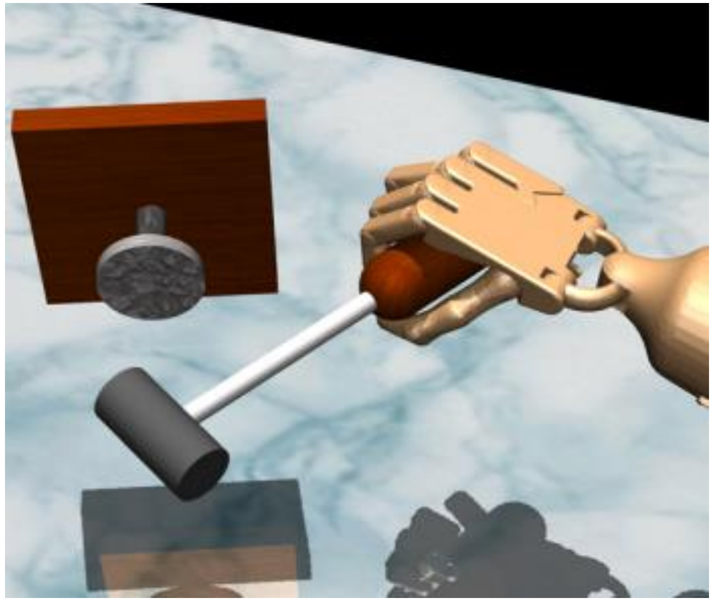

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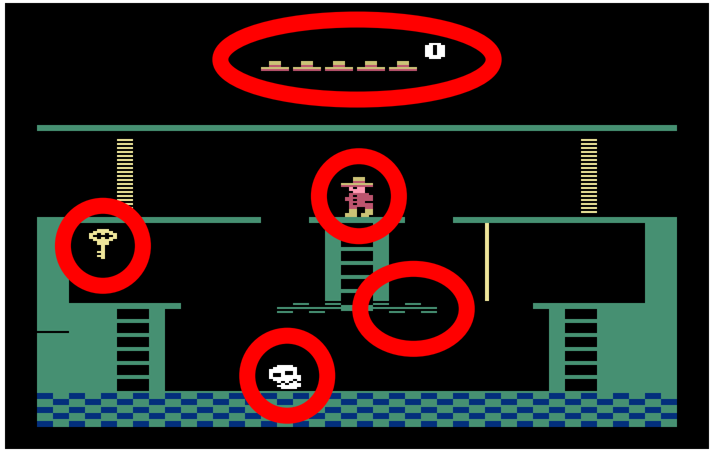

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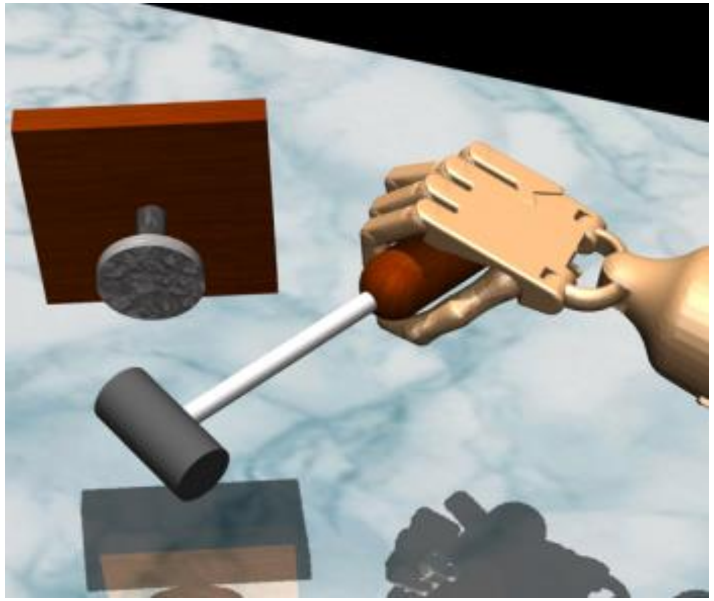

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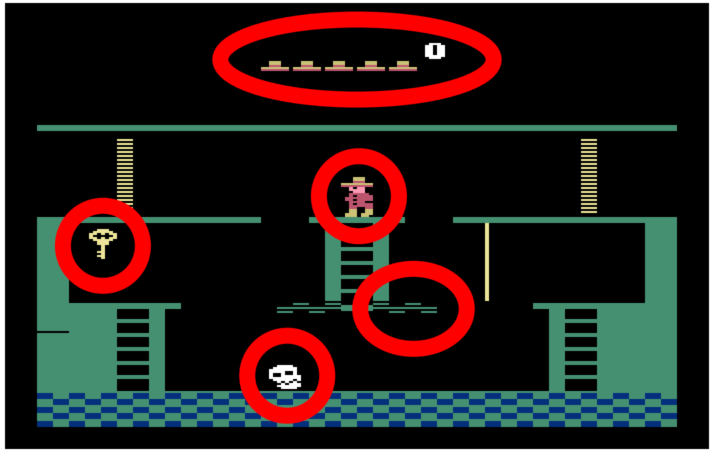

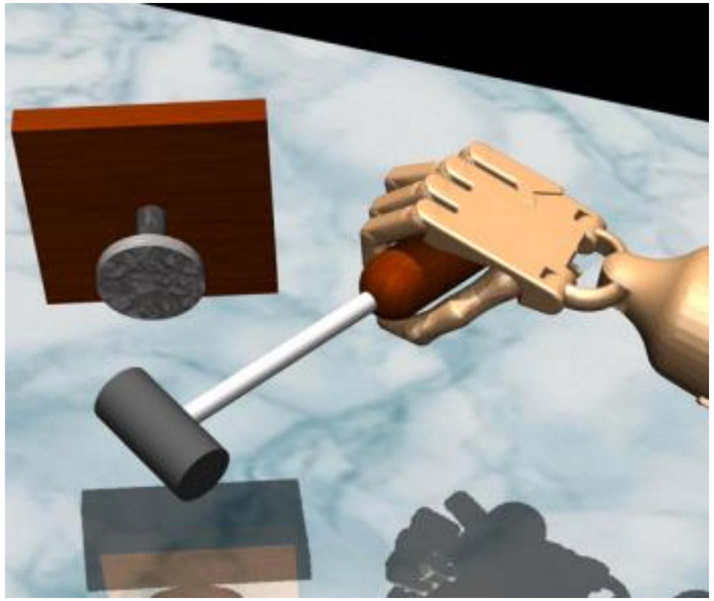

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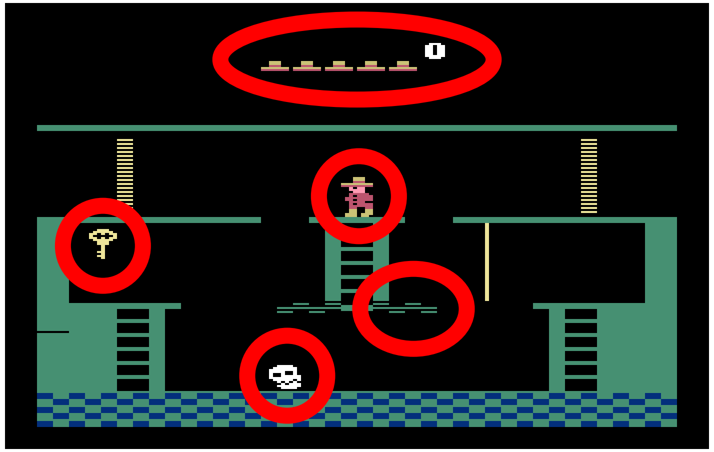
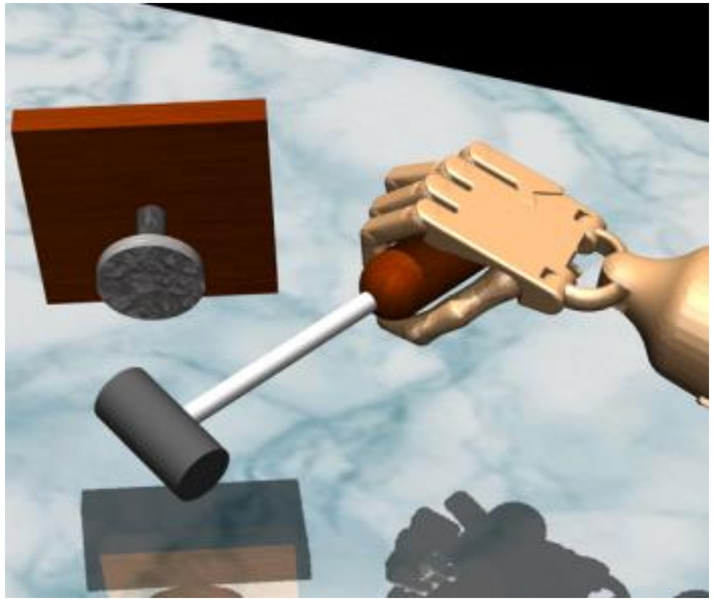
can we get $p_\theta(\mathbf{s})$ and $p_{\theta'}(\mathbf{s})$ to obey these equations?

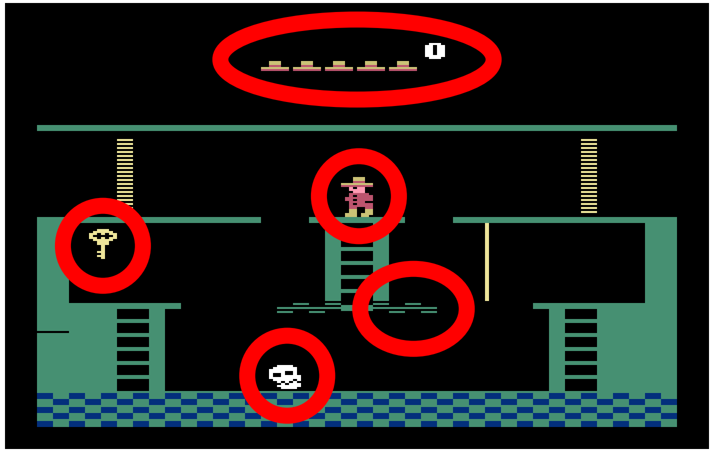
Exploring with pseudo-counts

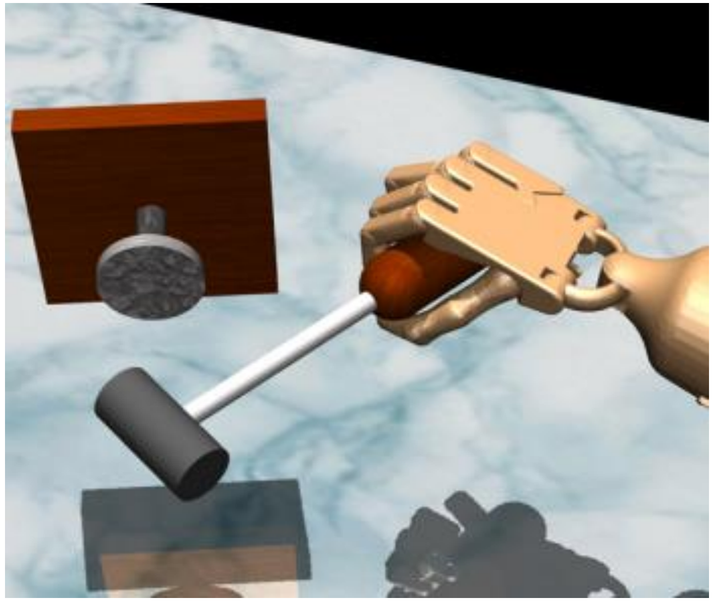




Bellemare et al. “Unifying Count-Based Exploration…”

Exploring with pseudo-counts

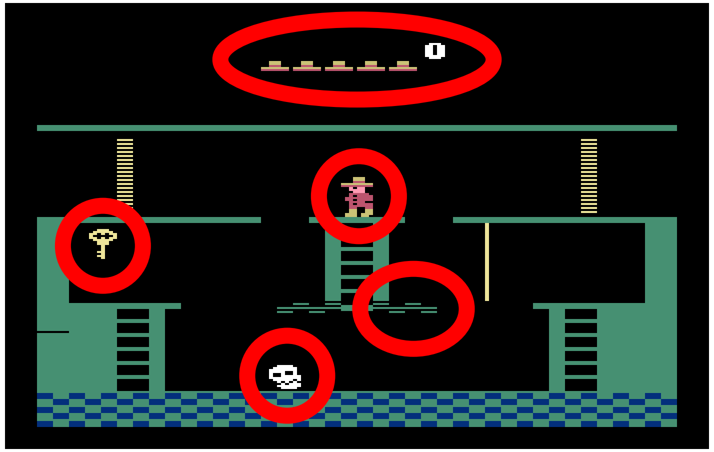


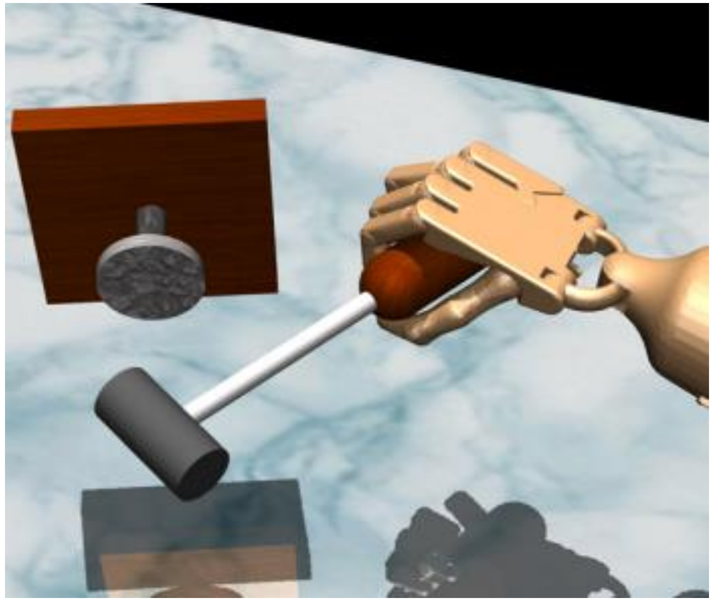


fit model $p_\theta(\mathbf{s})$ to all states $\mathcal{D}$ seen so far

Bellemare et al. "Unifying Count-Based Exploration…"

Exploring with pseudo-counts





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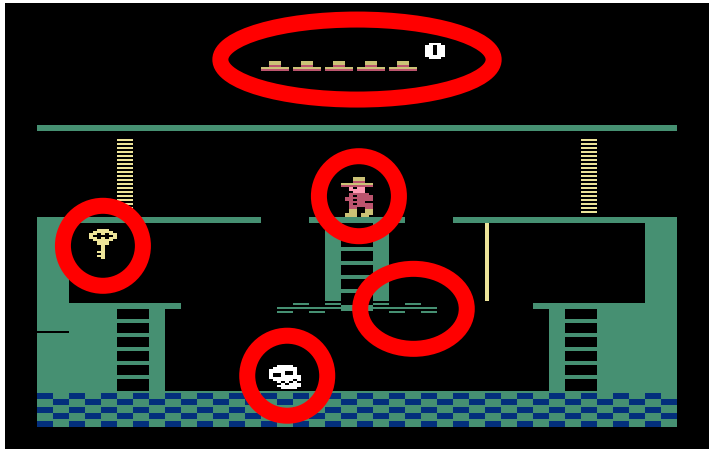

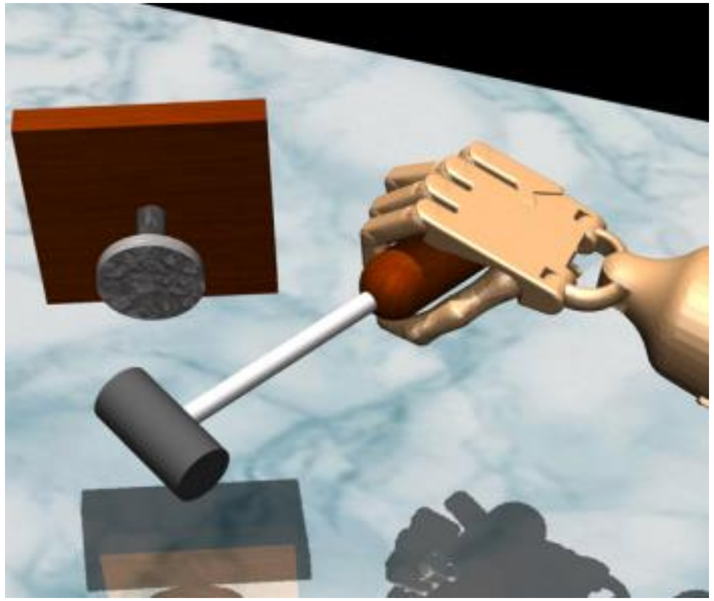

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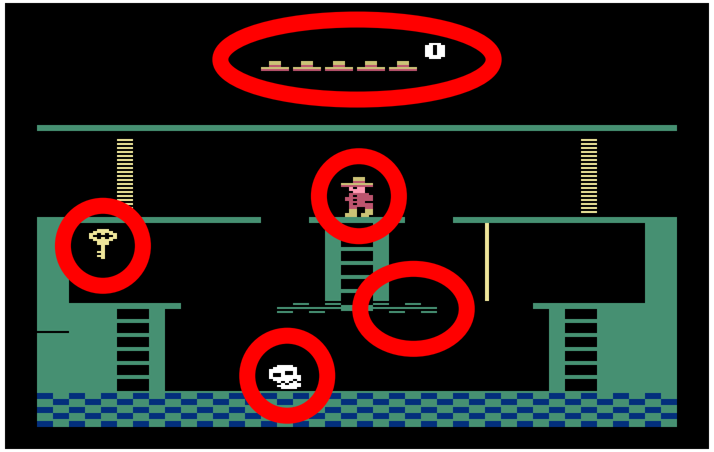

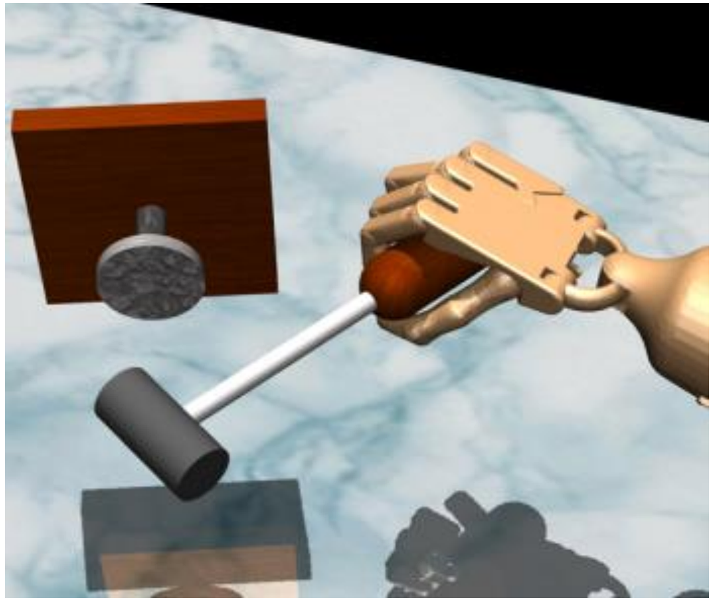

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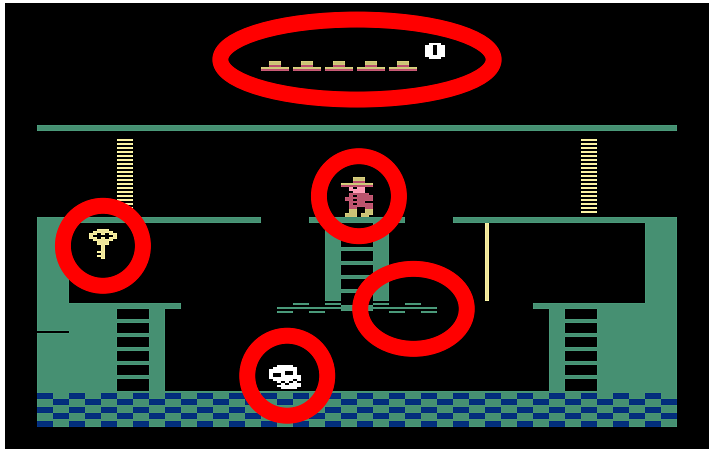
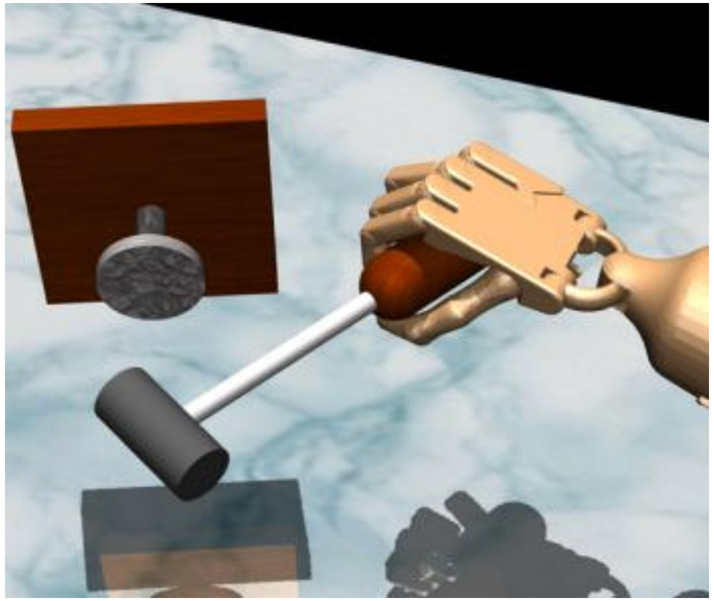
Bellemare et al. “Unifying Count-Based Exploration…”

Exploring with pseudo-counts





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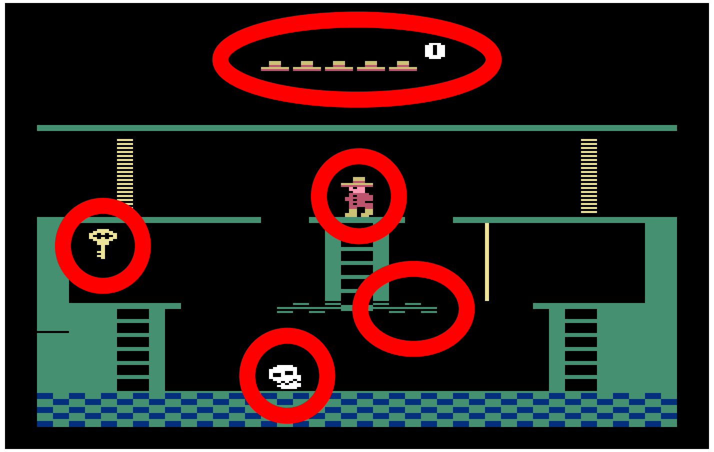
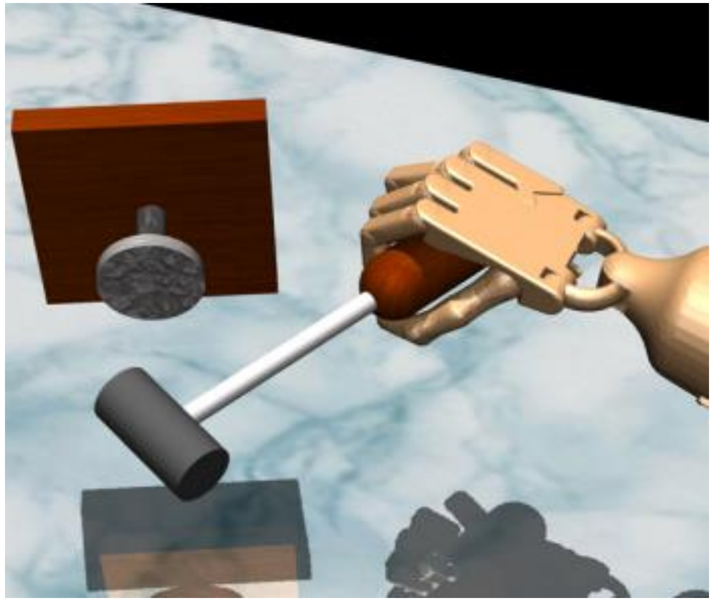
Bellemare et al. "Unifying Count-Based Exploration…"

Exploring with pseudo-counts





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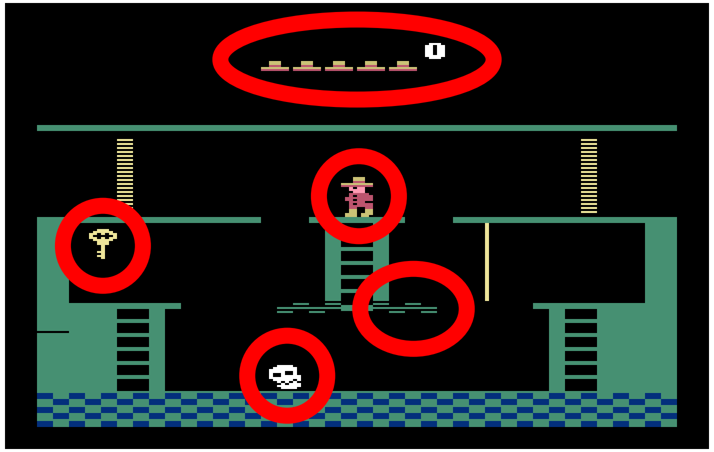
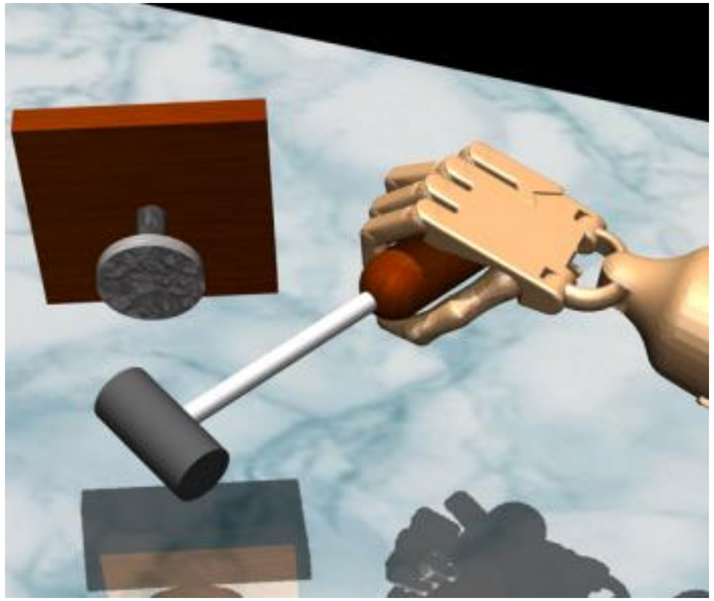
Bellemare et al. "Unifying Count-Based Exploration…"

Exploring with pseudo-counts





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Bellemare et al. "Unifying Count-Based Exploration…"

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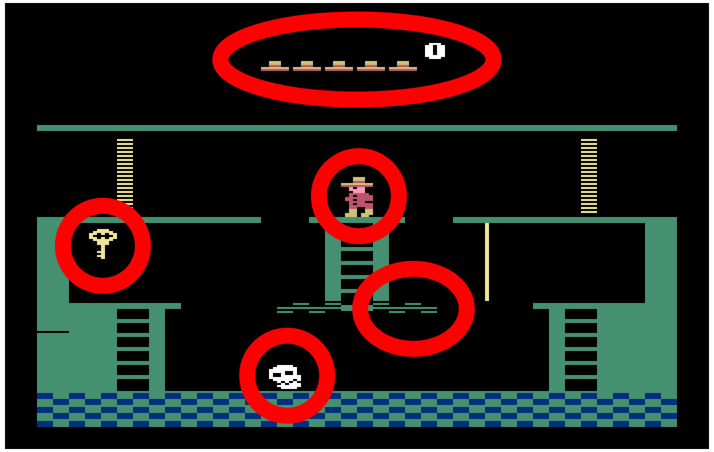

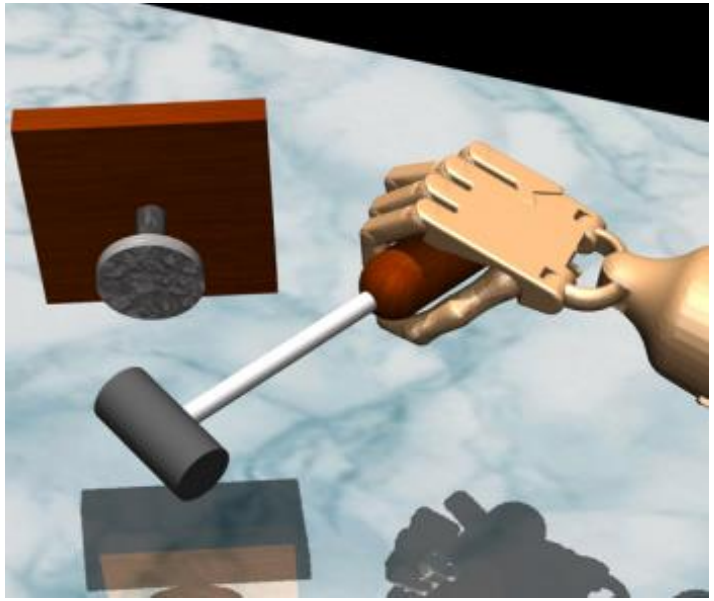

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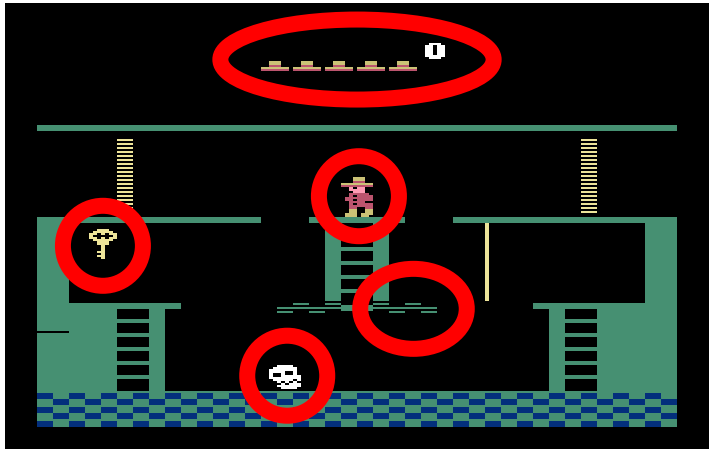
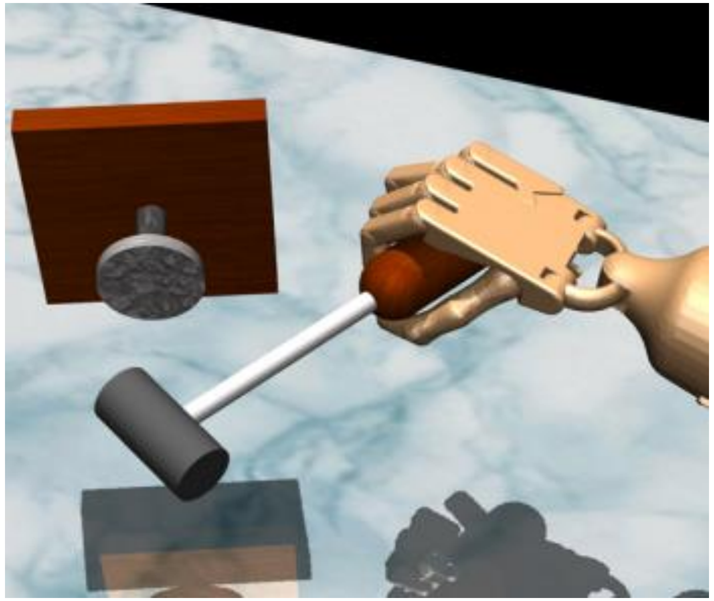
how to get $\hat{N}(\mathbf{s})$? use the equations

Bellemare et al. "Unifying Count-Based Exploration…"

Exploring with pseudo-counts





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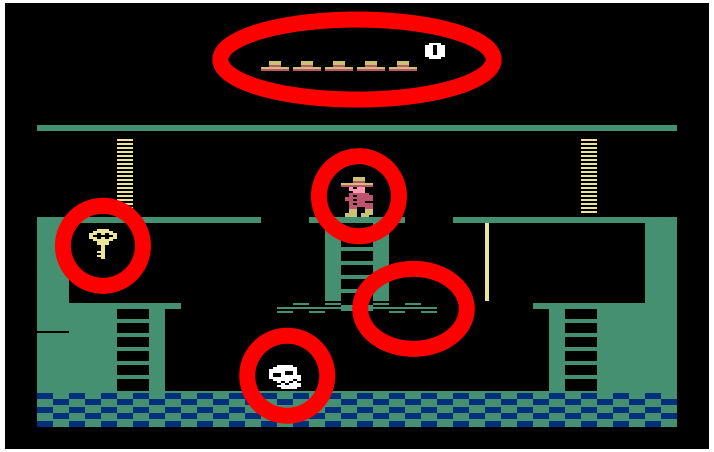
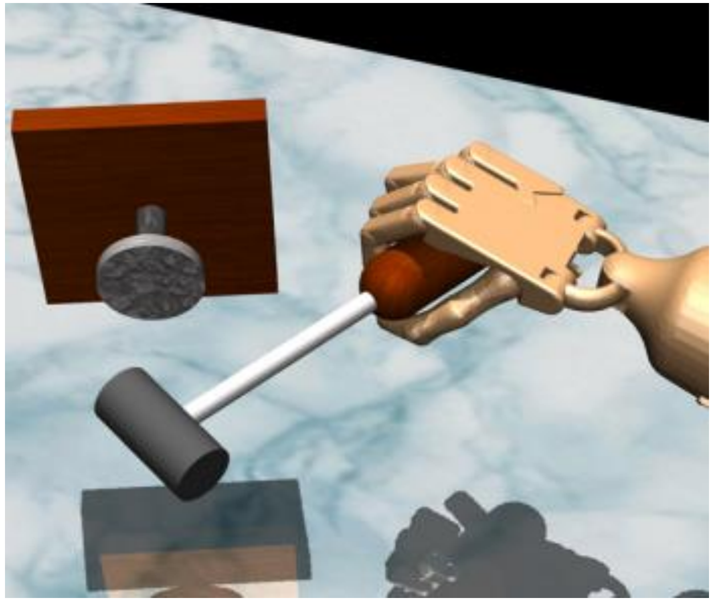
$$p_\theta(\mathbf{s}_i) = \frac{\hat{N}(\mathbf{s}_i)}{\hat{n}} \qquad p_{\theta'}(\mathbf{s}_i) = \frac{\hat{N}(\mathbf{s}_i) + 1}{\hat{n} + 1}$$

Bellemare et al. "Unifying Count-Based Exploration…"

Exploring with pseudo-counts





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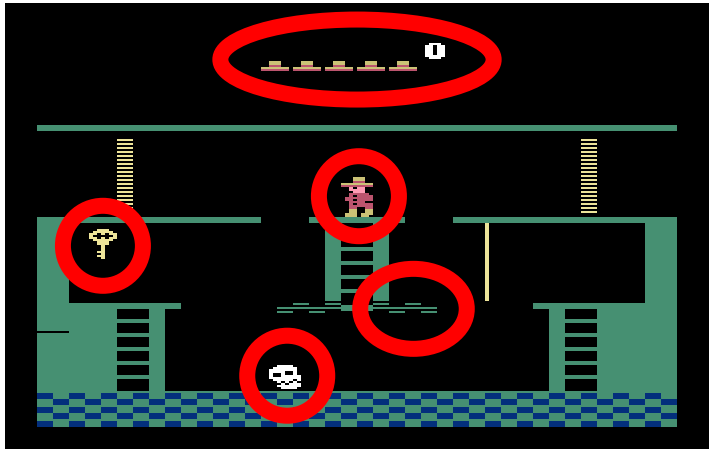
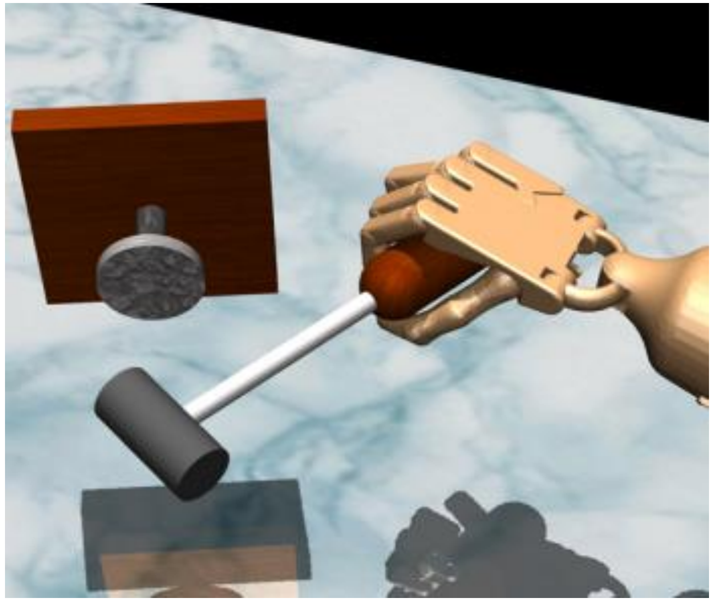
two equations and two unknowns!

Bellemare et al. "Unifying Count-Based Exploration…"

Exploring with pseudo-counts





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two equations and two unknowns!

$$\hat{N}(\mathbf{s}_i) = \hat{n} p_\theta(\mathbf{s}_i) \qquad\qquad \hat{n} = \frac{1 - p_{\theta'}(\mathbf{s}_i)}{p_{\theta'}(\mathbf{s}_i) - p_\theta(\mathbf{s}_i)} p_\theta(\mathbf{s}_i)$$

Bellemare et al. "Unifying Count-Based Exploration…"

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Lots of functions in the literature, inspired by optimal methods for bandits or small MDPs

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What kind of bonus to use?

Lots of functions in the literature, inspired by optimal methods for bandits or small MDPs

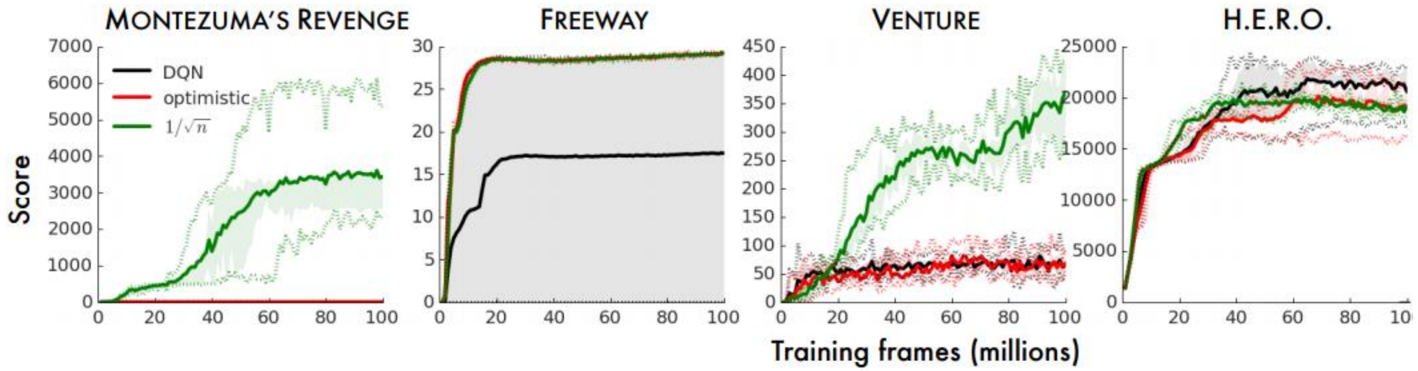
UCB: $$\mathcal{B}(N(\mathbf{s})) = \sqrt{\frac{2 \ln n}{N(\mathbf{s})}}$$

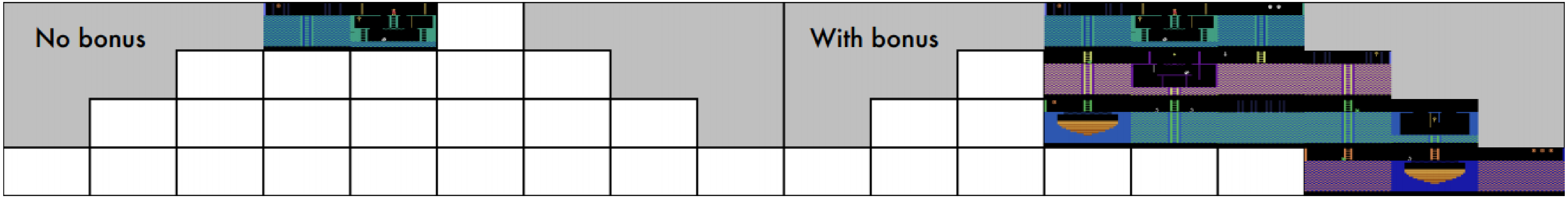
MBIE-EB (Strehl & Littman, 2008): $$\mathcal{B}(N(\mathbf{s})) = \sqrt{\frac{1}{N(\mathbf{s})}}$$

this is the one used by Bellemare et al. '16

BEB (Kolter & Ng, 2009): $$\mathcal{B}(N(\mathbf{s})) = \frac{1}{N(\mathbf{s})}$$

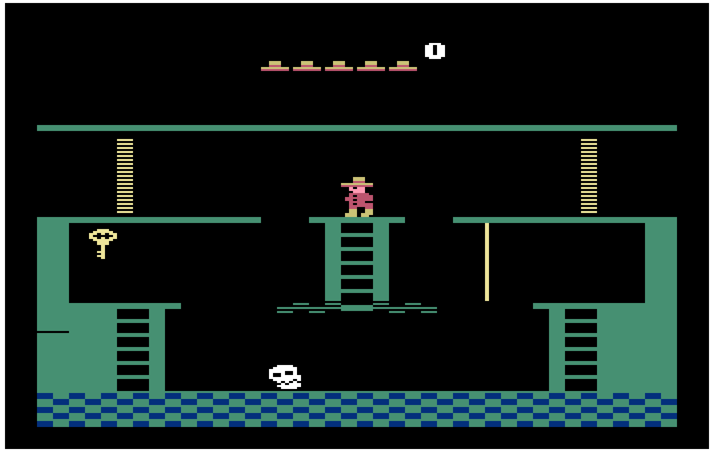
Does it work?

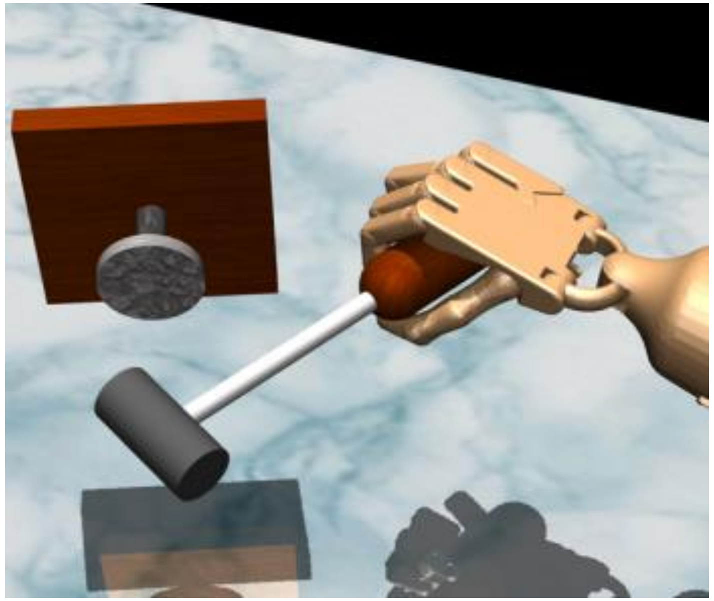




Bellemare et al. "Unifying Count-Based Exploration…"

What kind of model to use?





$$p_\theta(\mathbf{s})$$

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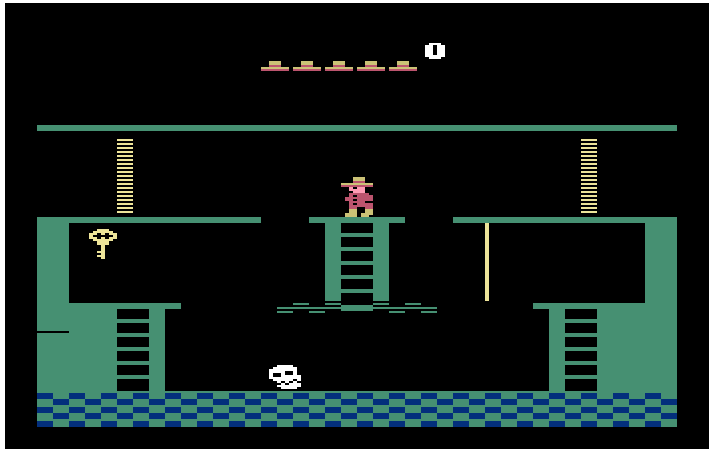

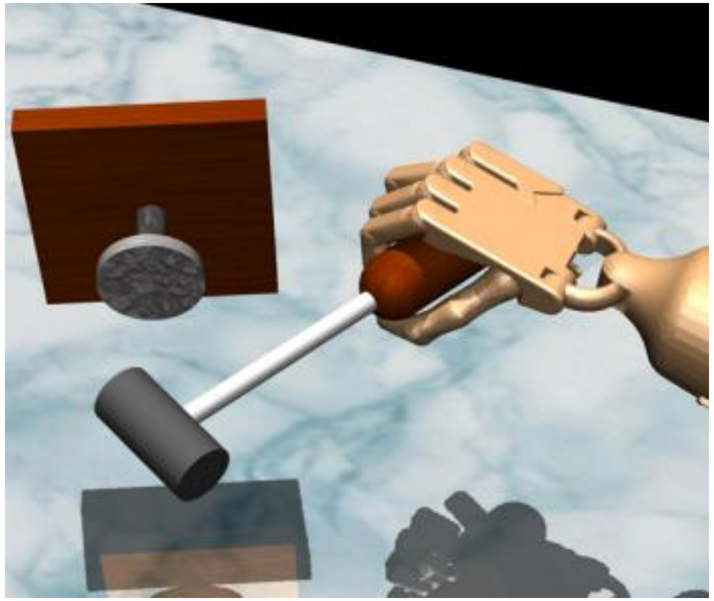

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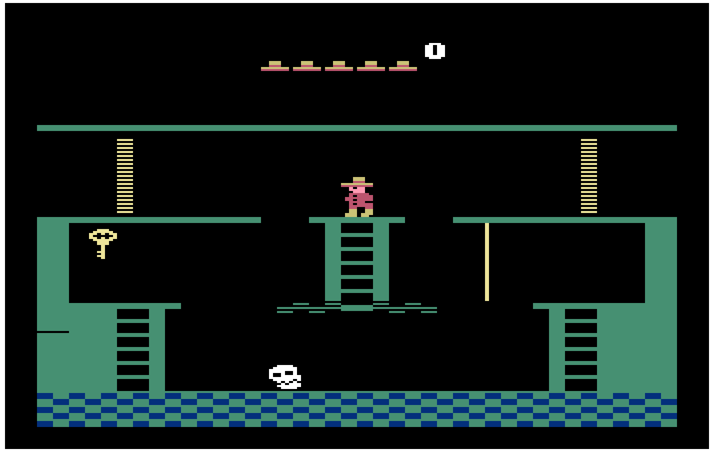

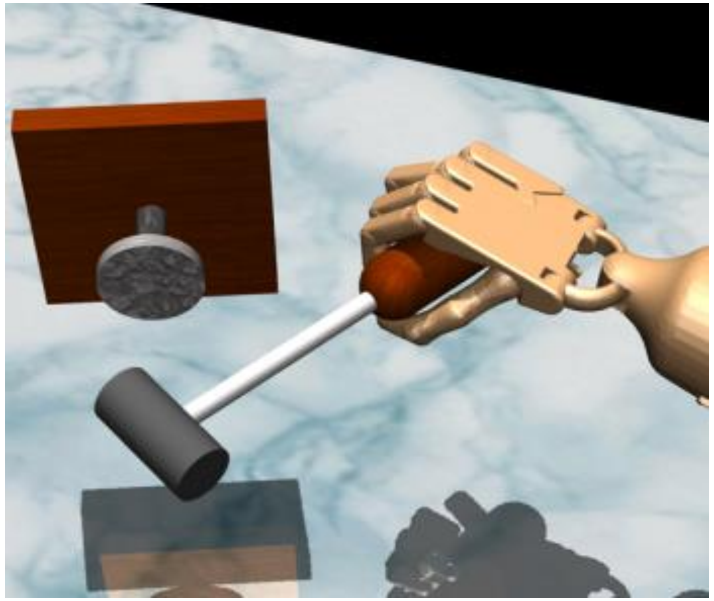

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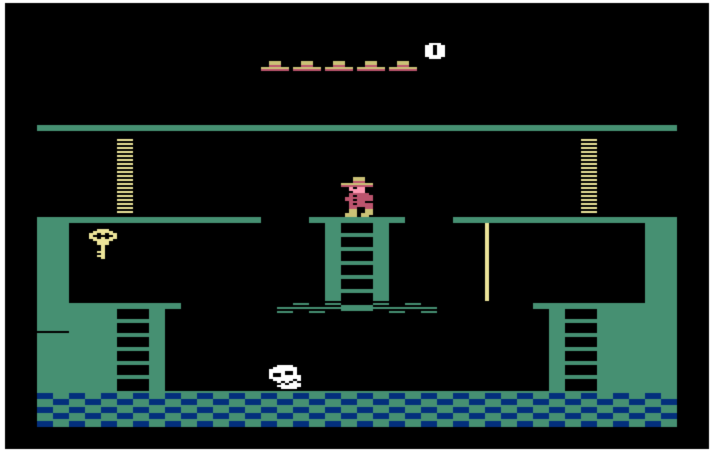

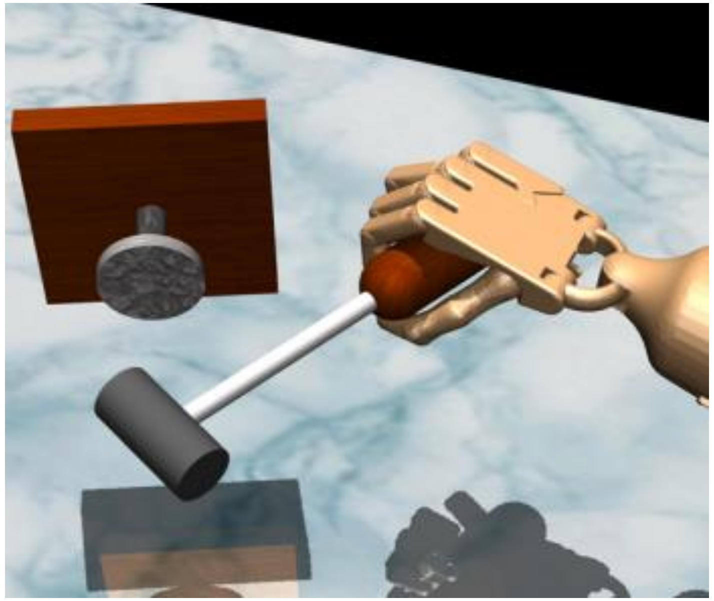

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Bellemare et al.: "CTS" model: condition each pixel on its top-left neighborhood

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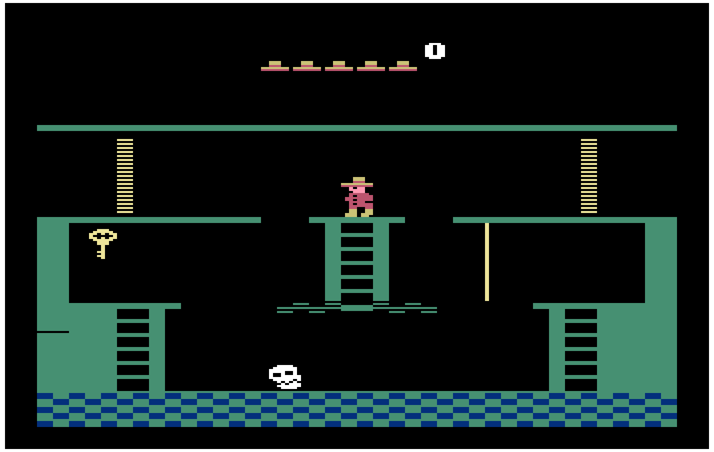

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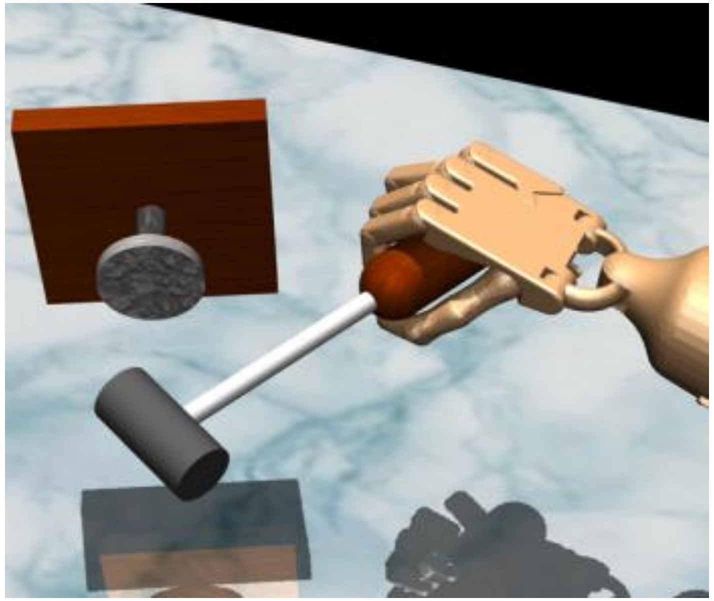

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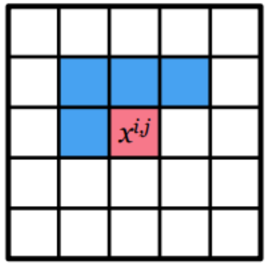

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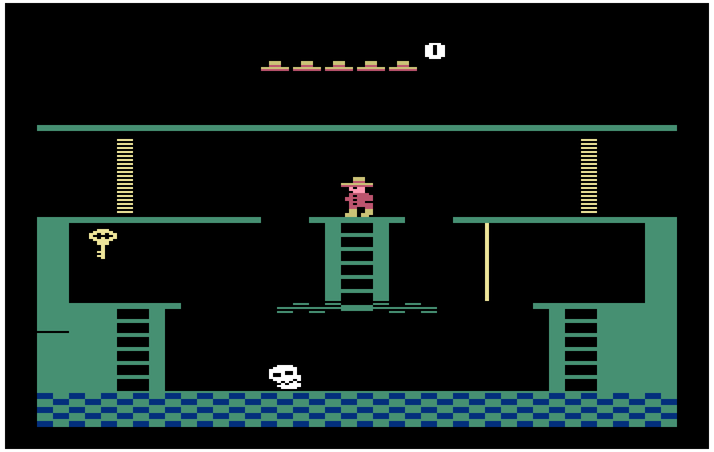

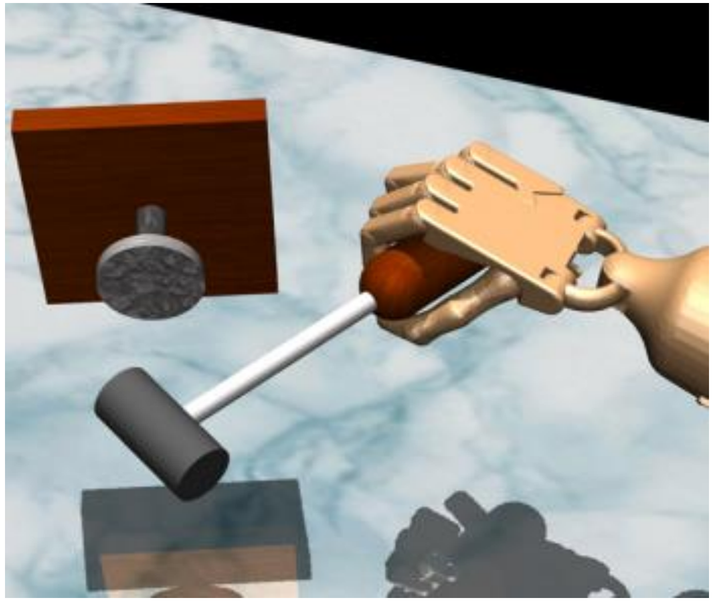

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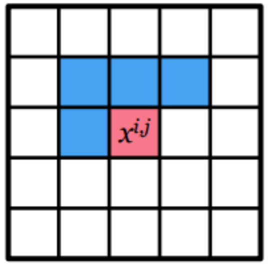

Other models: stochastic neural networks, compression length, EX2

Posterior sampling in deep RL

Represent explicitly our uncertainty in the model parameters θ

Then sample from it (Thompson sampling):

$$\theta_1, \ldots, \theta_n \sim \hat{p}(\theta_1, \ldots, \theta_n)$$

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Osband et al. "Deep Exploration via Bootstrapped DQN"

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since Q-learning is off-policy, we don't care which Q-function was used to collect data

Osband et al. "Deep Exploration via Bootstrapped DQN"

Bootstrap

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given a dataset $\mathcal{D}$, resample with replacement N times to get $\mathcal{D}_1, \ldots, \mathcal{D}_N$

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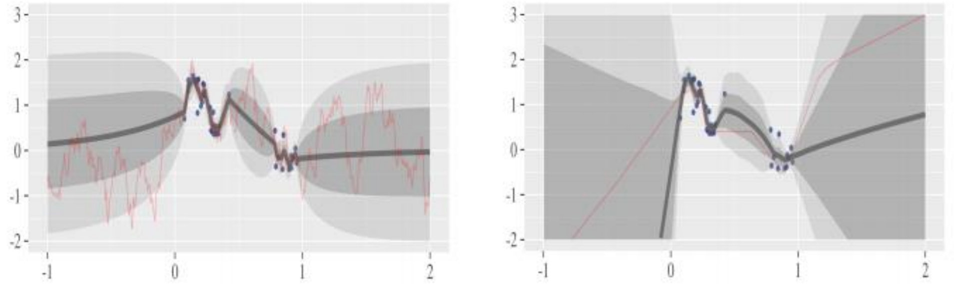

(b) Gaussian process posterior (c) Bootstrapped neural nets

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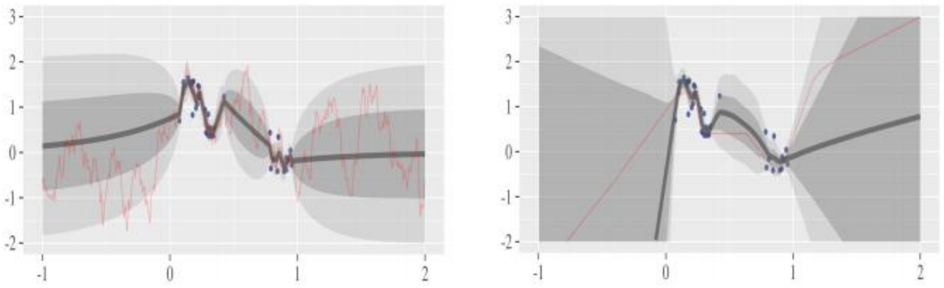

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training N big neural nets is expensive, can we avoid it?

Osband et al. "Deep Exploration via Bootstrapped DQN"

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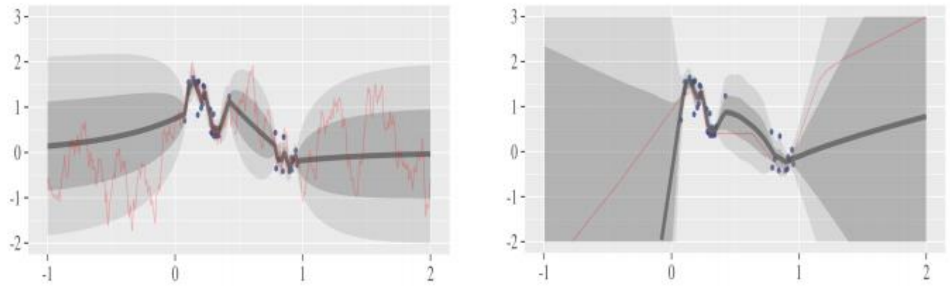

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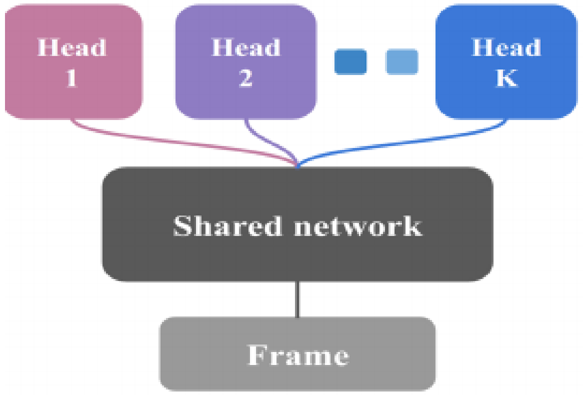
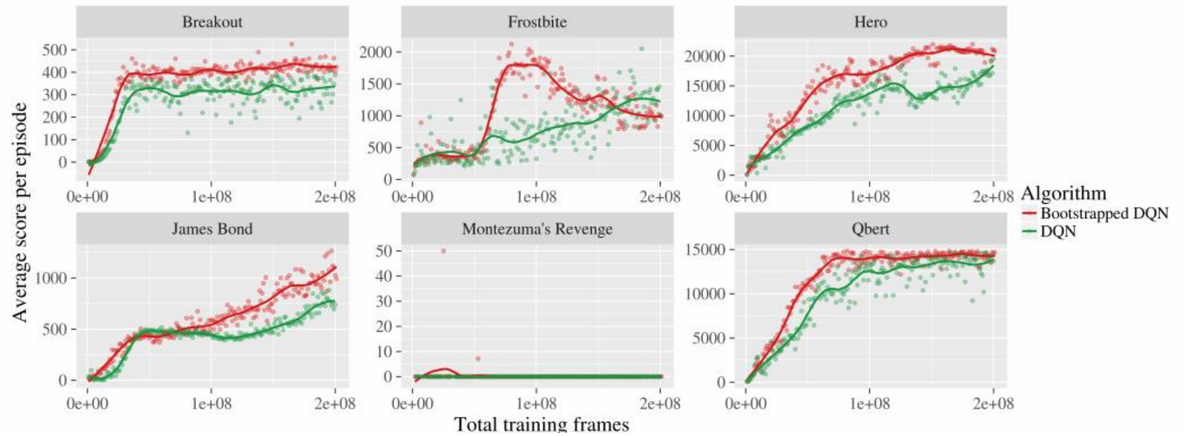


Osband et al. "Deep Exploration via Bootstrapped DQN"

Why does this work?

Exploring with random actions (e.g., epsilon-greedy): random walk pattern, in general $\Omega(N^2)$ steps to visit N states.

Exploring with random Q-functions: commit to a randomized but internally consistent strategy ***for an entire episode***

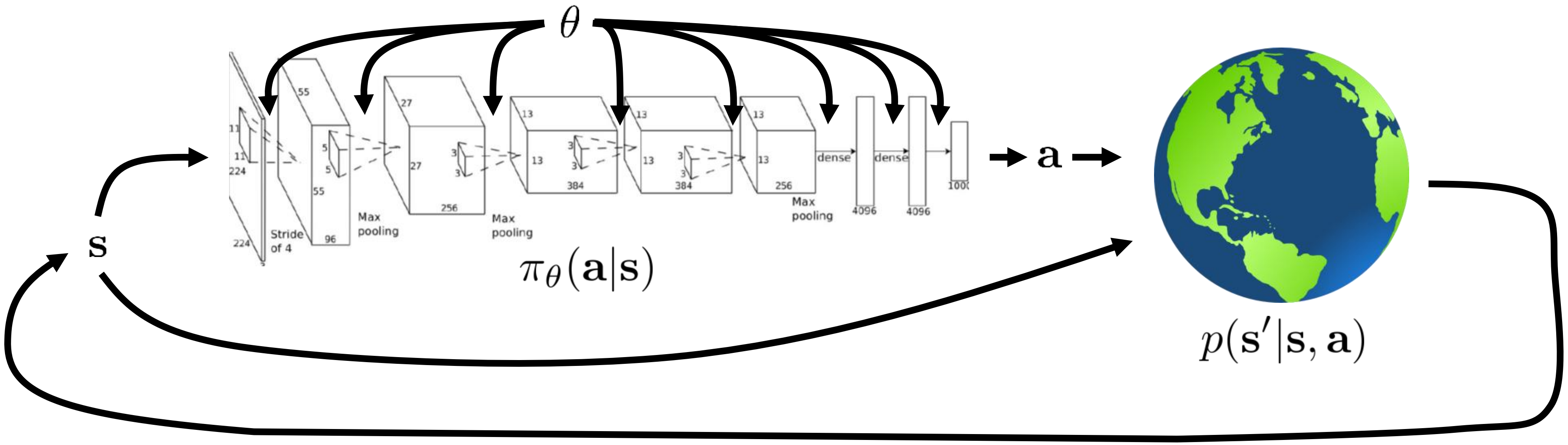


+ no change to original reward function

- very good bonuses often do better

Osband et al. "Deep Exploration via Bootstrapped DQN"

Recap: model-free reinforcement learning



$$\underbrace{p_\theta(\mathbf{s}_1,\mathbf{a}_1,\ldots,\mathbf{s}_T,\mathbf{a}_T)}_{\pi_\theta(\tau)} = p(\mathbf{s}_1)\prod_{t=1}^{T}\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)p(\mathbf{s}_{t+1}|\mathbf{s}_t,\mathbf{a}_t)$$

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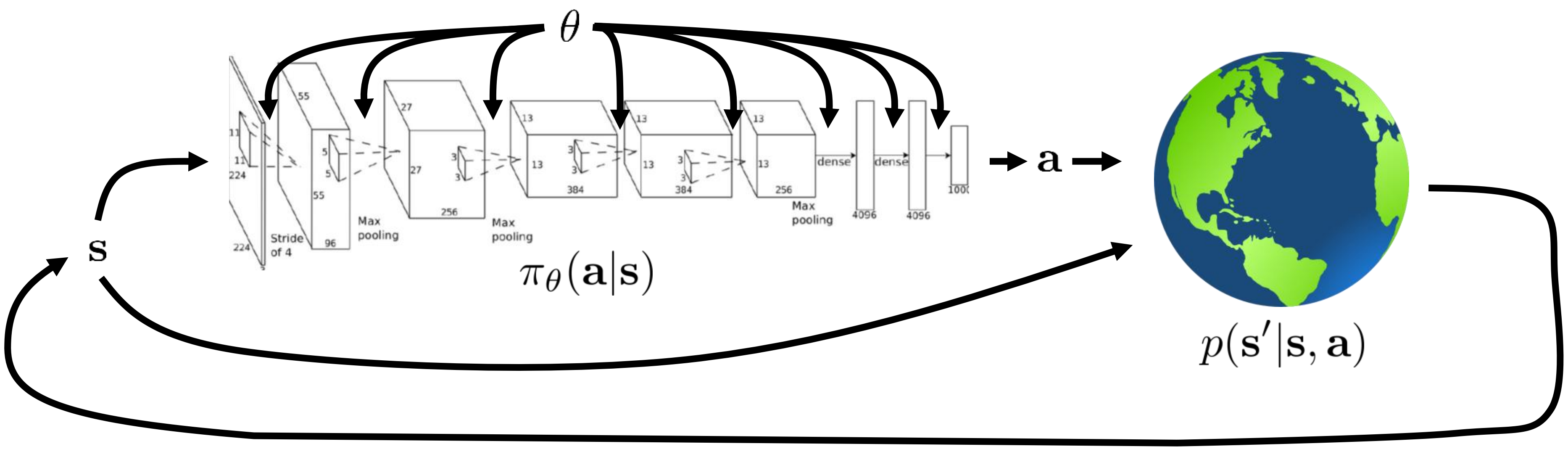

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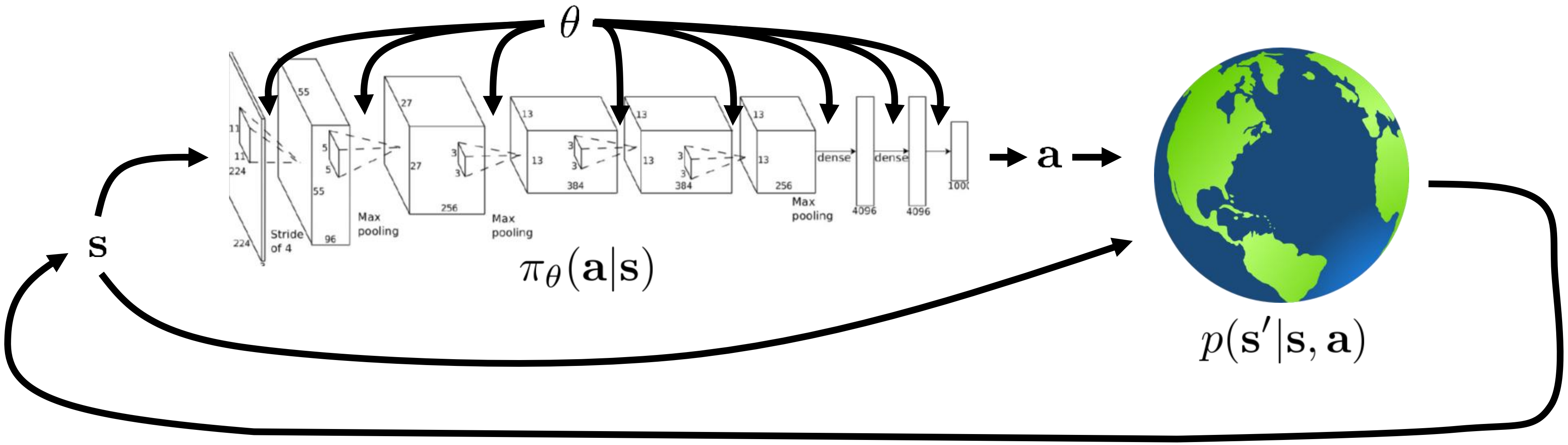

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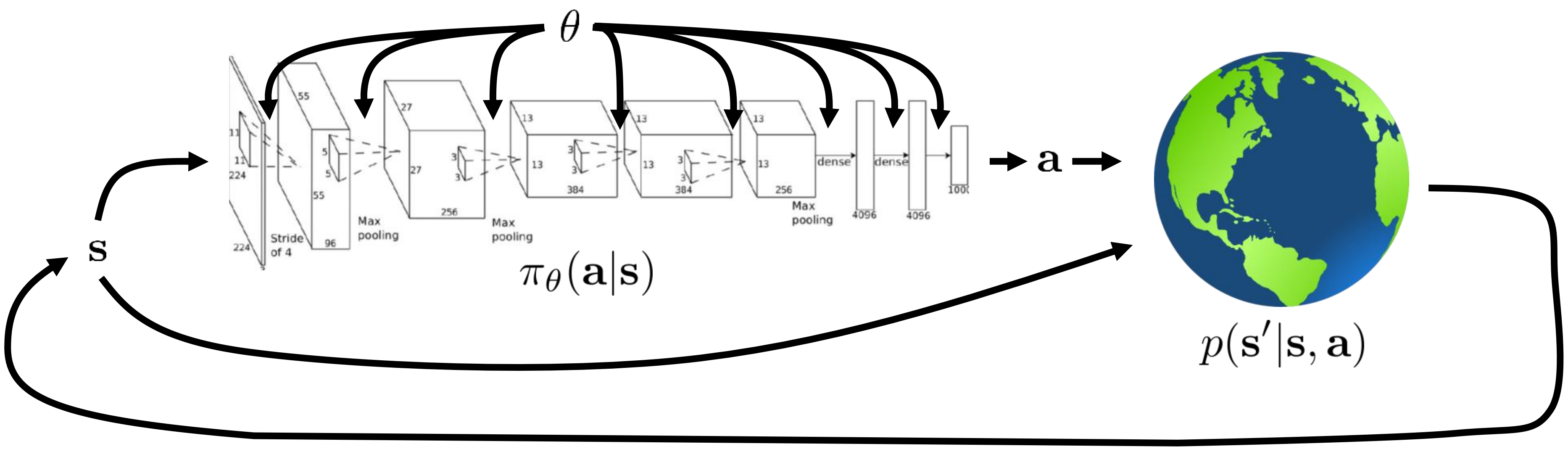

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don't even attempt to learn it

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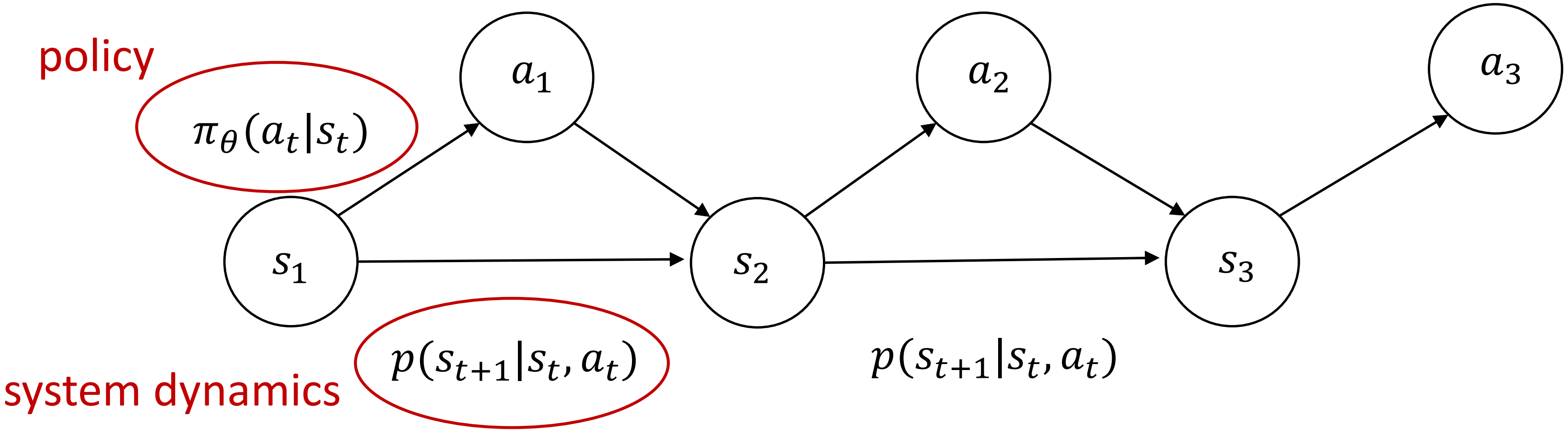
Does knowing the dynamics make things easier?

Often, yes!

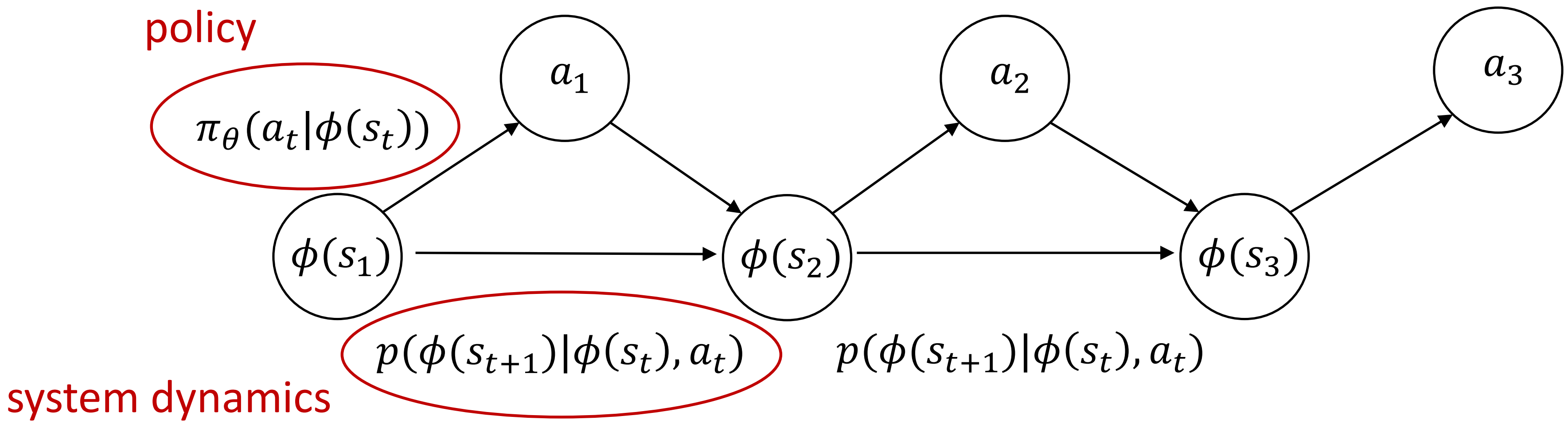
Model-based reinforcement learning

1. Model-based reinforcement learning: learn the transition dynamics, then figure out how to choose actions
2. Advantages:
    1. Avoid making expensive real-world or simulator actions
    2. Possibly differentiate through the dynamics to optimize action choice
3. We then have an optimal control problem



Simplifying Model-based reinforcement learning

1. Computing a complete environment model can be very expensive (has to generate images for vision-based policies)
2. Do we really need the full state?
3. Is there a simplified function of the state $\phi(s)$ that's sufficient for RL?
4. Should be sufficient to predict next state and for policy to choose next action.



Curiosity-driven Exploration by Self-supervised Prediction

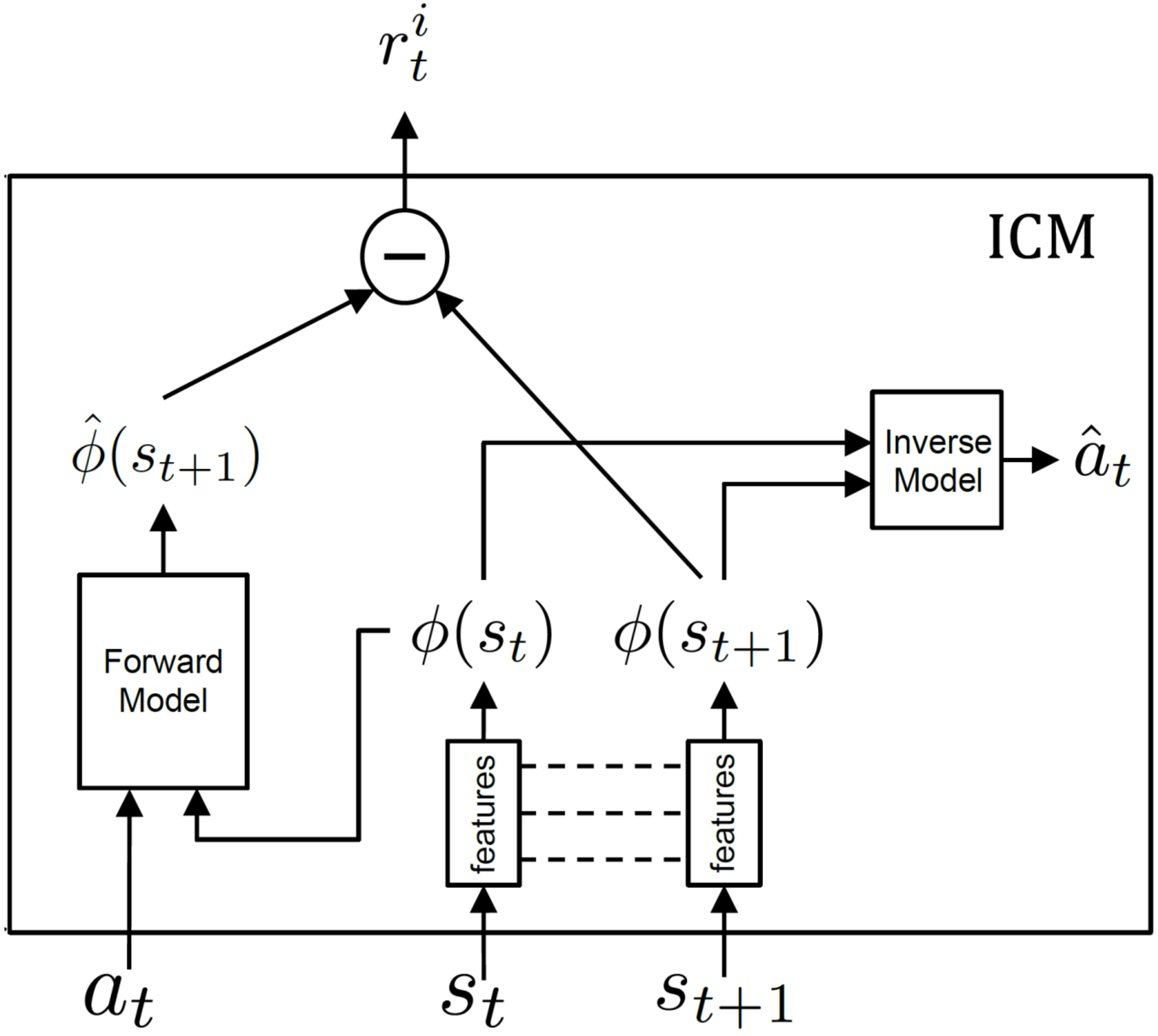
Pathak et al. 2017

1. Computes a simplified environment model $\phi(s_t)$
2. Uses error in the model's prediction to highlight states that need further exploration.

Intrinsic Curiosity Model (ICM)

Pathak et al. 2017

1. Uses an inverse model to ensure $\phi(s_t)$ is sufficient for action selection.
2. Estimates a forward model for next state.
3. The forward model error is the curiosity signal.

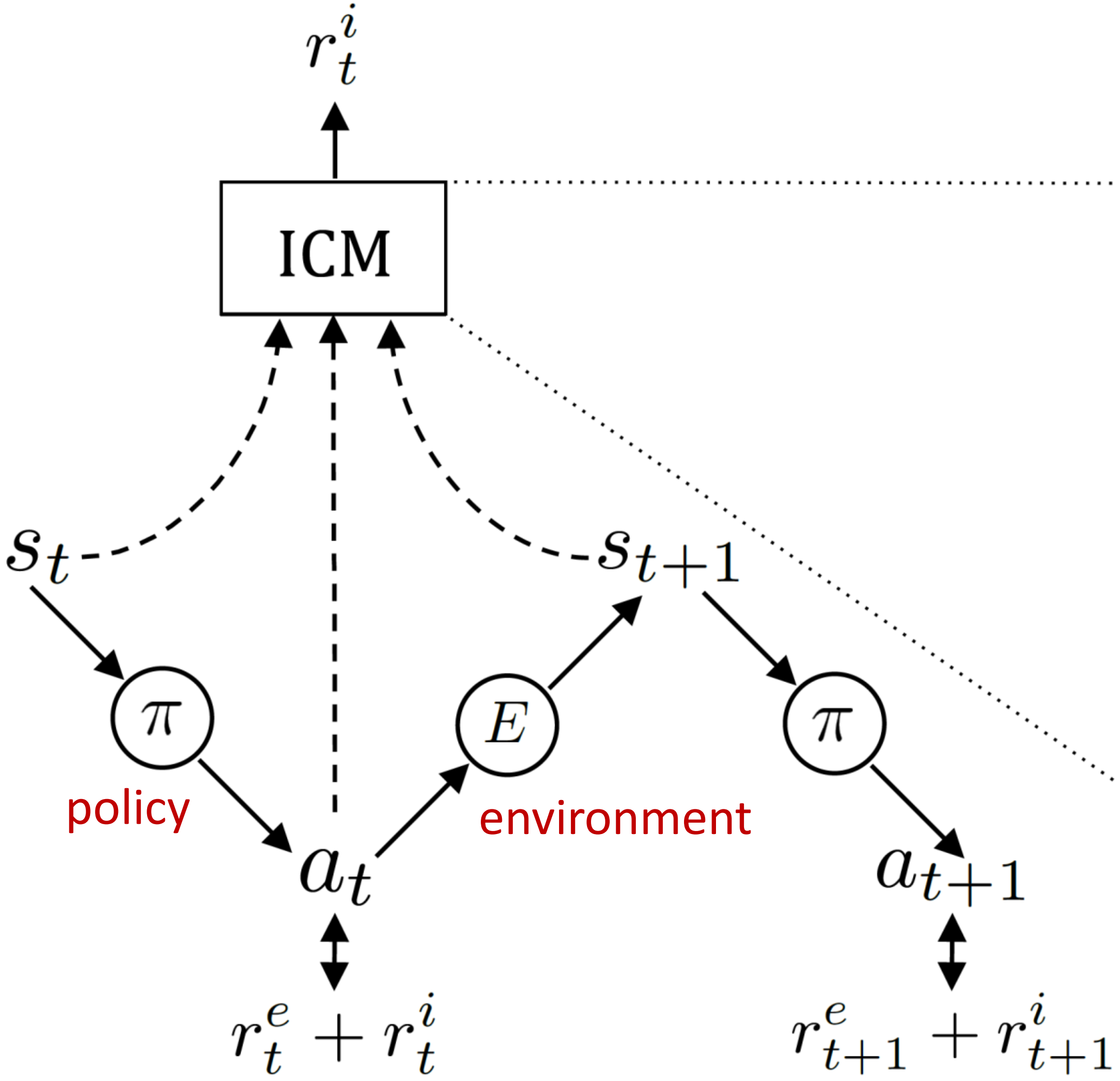


Curiosity-Driven Exploration

Pathak et al. 2017

1. The ICM provides an intrinsic reward signal r_t^i.

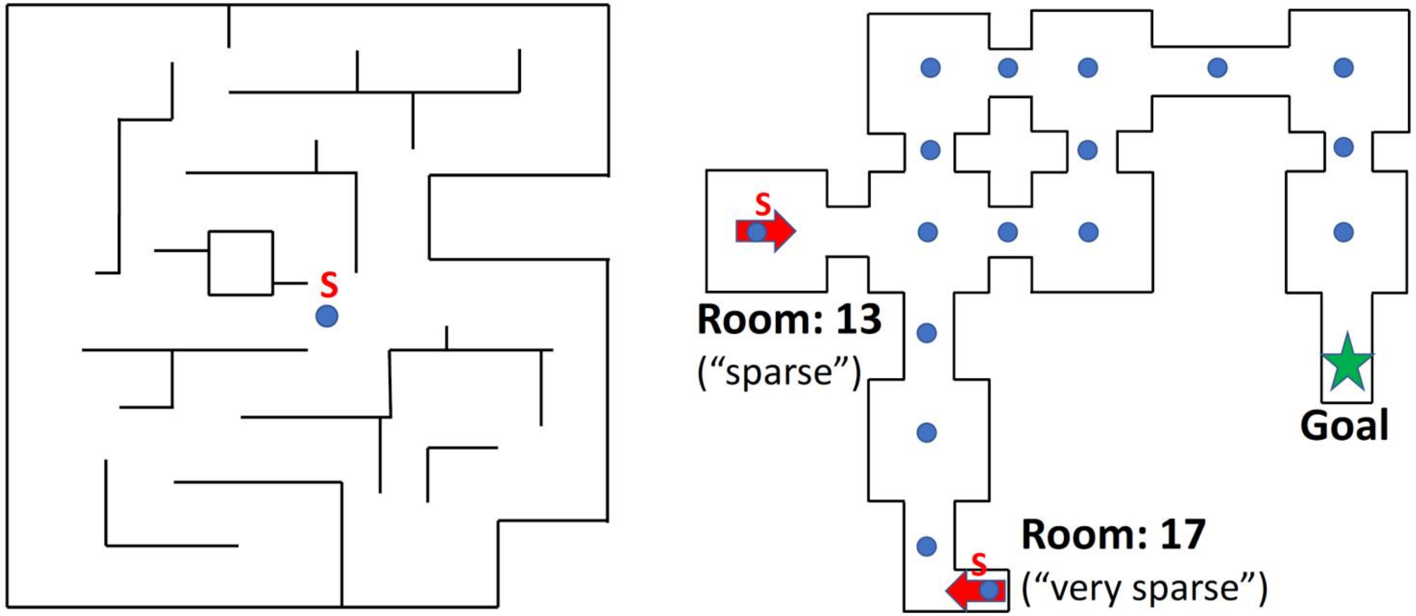
2. The policy can be trained by any RL method using the combined reward.



Curiosity-Driven Exploration

Pathak et al. 2017

Environments: Vizdoom

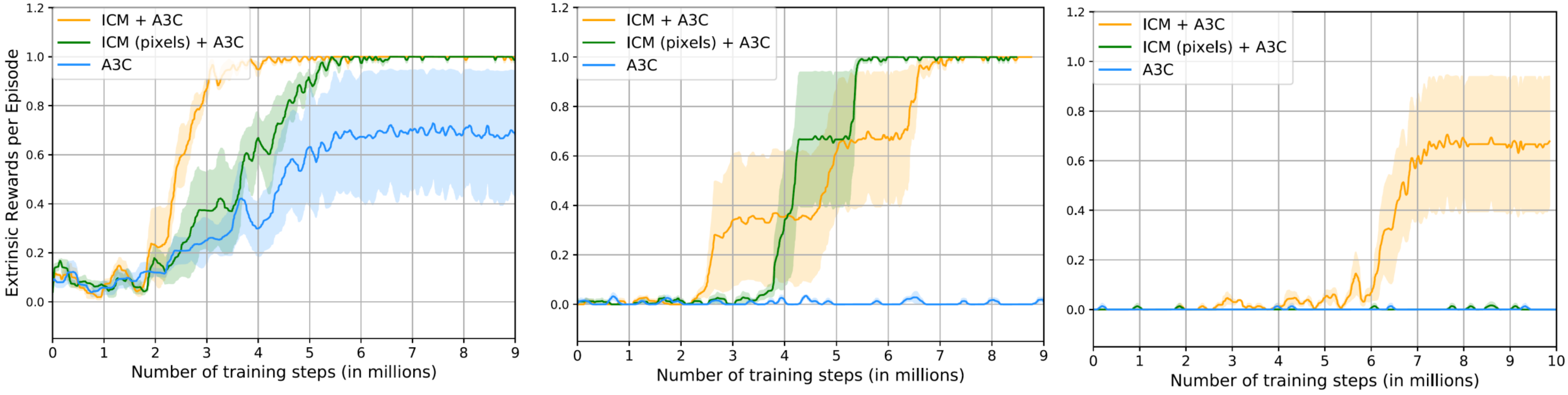


(a) Train Map Scenario (b) Test Map Scenario

Model is trained initially without goal reward (left). Agent is randomly started on one of the blue dots in the "dense" case (right).

Curiosity-Driven Exploration

Pathak et al. 2017



(a) "dense reward" setting

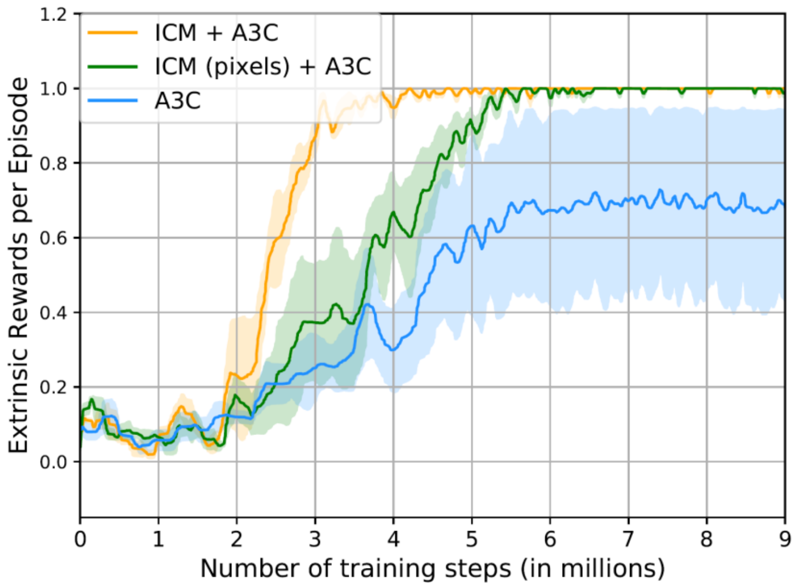
(b) "sparse reward" setting

(c) "very sparse reward" setting

Curiosity-Driven Exploration

Pathak et al. 2017

Relative performance improves as reward sparseness increases.



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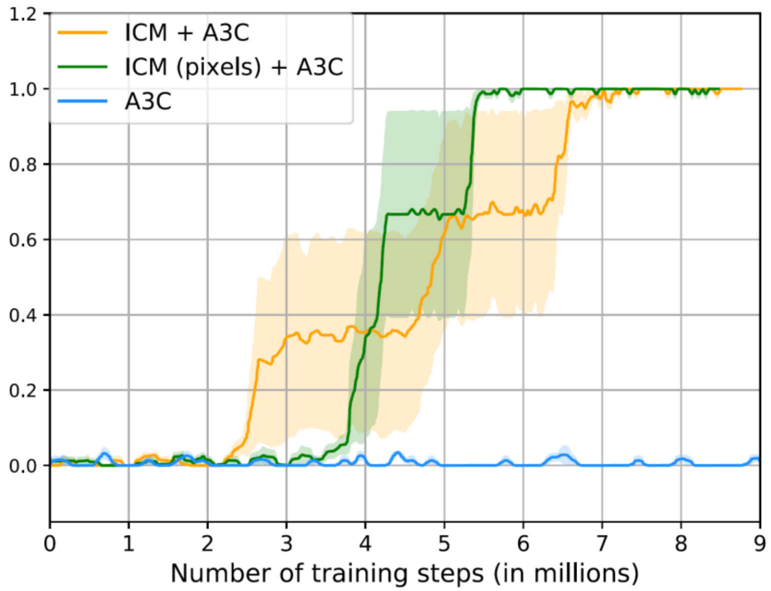
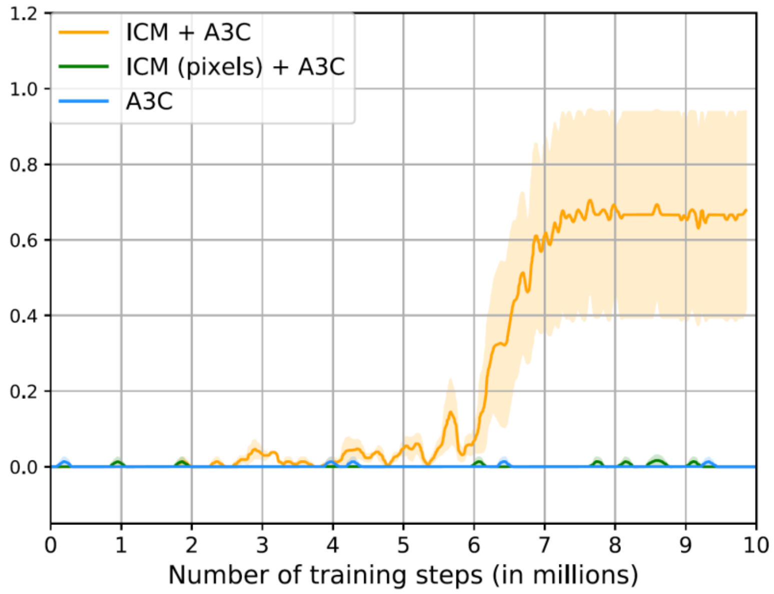
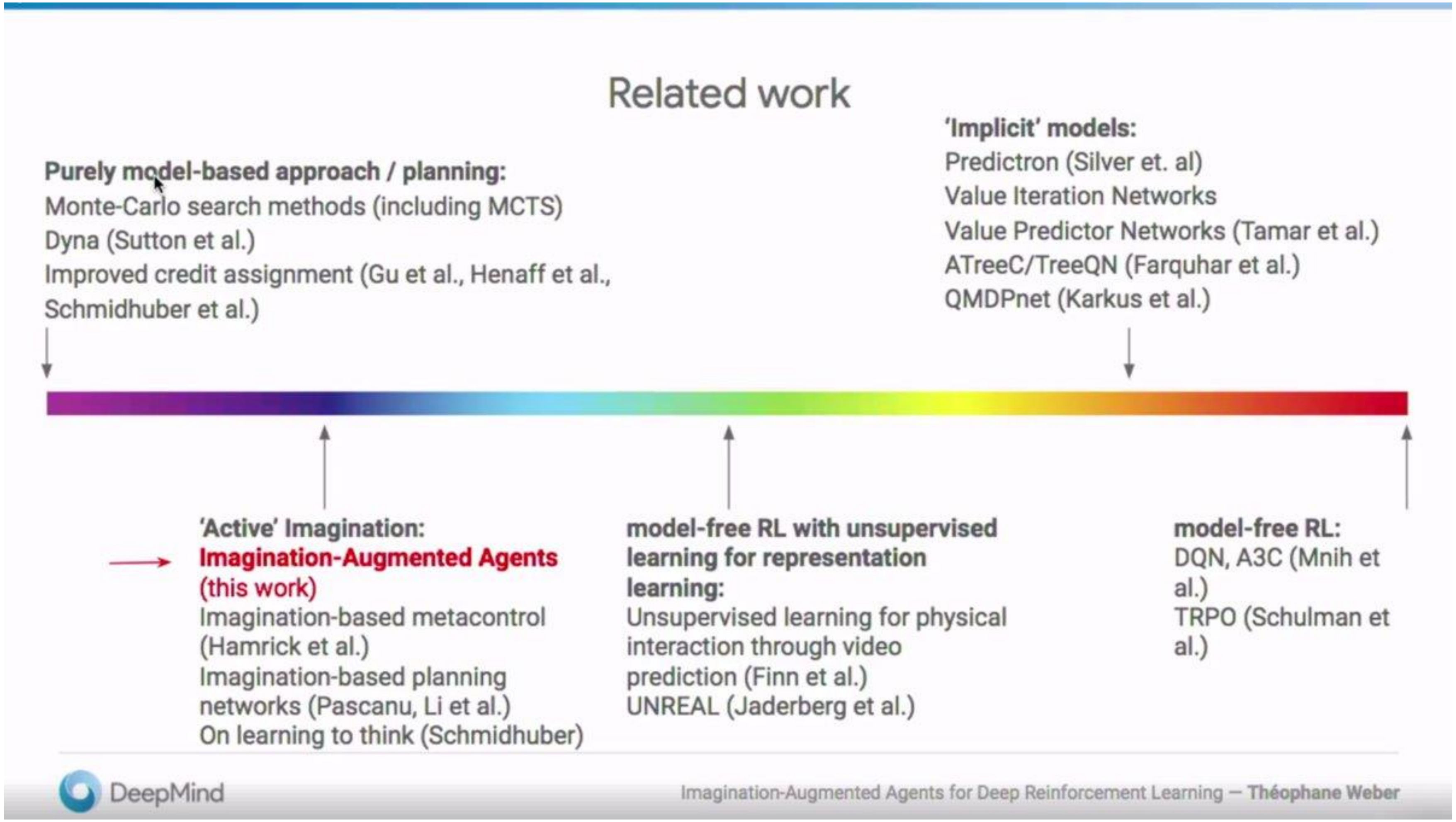


(b) "sparse reward" setting



(c) "very sparse reward" setting

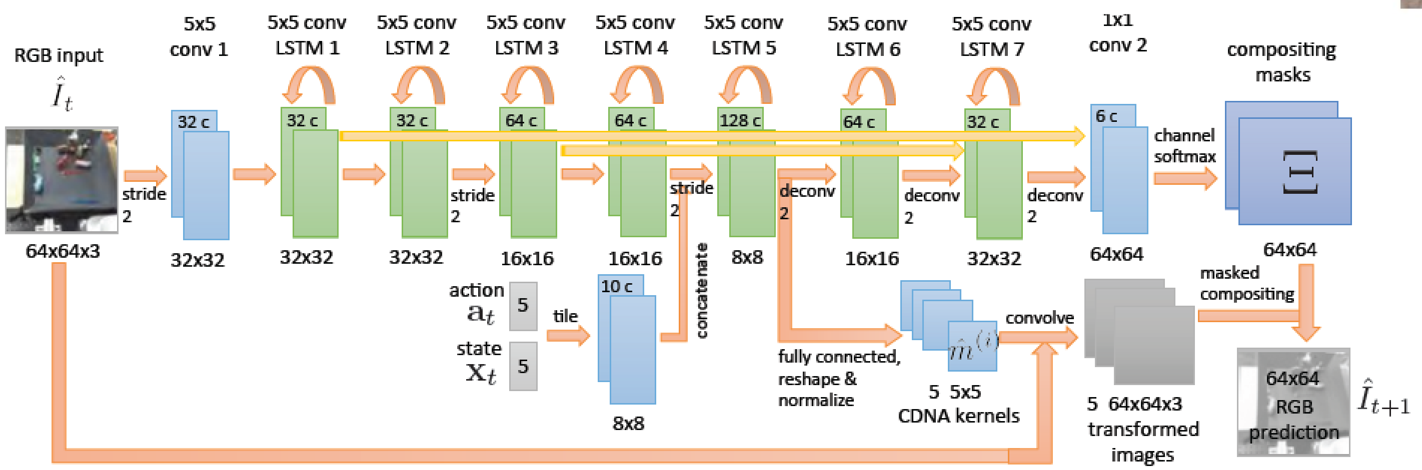
Model-Free vs Model-Based (Theophane Weber)

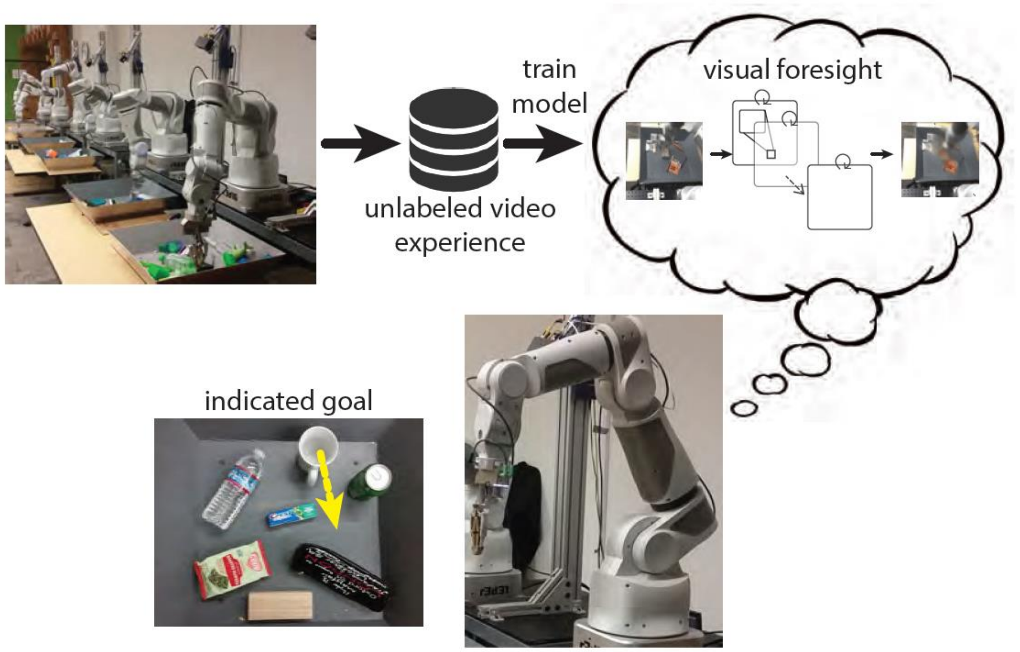


Model-Free vs Model-Based

Video predictive models, e.g.
"Deep Visual Foresight for Planning Robot Motion" by Finn et al.

Pixel-level recurrent image prediction:





Computes a flow (motion) map across the image.

Optimizes action choice using CEM (Cross-Entropy Method).

Aside: Stochastic optimization

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abstract away optimal control/planning:

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$$\mathbf{a}_1, \ldots, \mathbf{a}_T = \arg \max_{\mathbf{a}_1, \ldots, \mathbf{a}_T} J(\mathbf{a}_1, \ldots, \mathbf{a}_T)$$

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$$\mathbf{a}_1, \ldots, \mathbf{a}_T = \arg\max_{\mathbf{a}_1, \ldots, \mathbf{a}_T} \underbrace{J(\mathbf{a}_1, \ldots, \mathbf{a}_T)}_{\text{don't care what this is}}$$

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simplest method: guess & check "random shooting method"

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Cross-entropy method (CEM)

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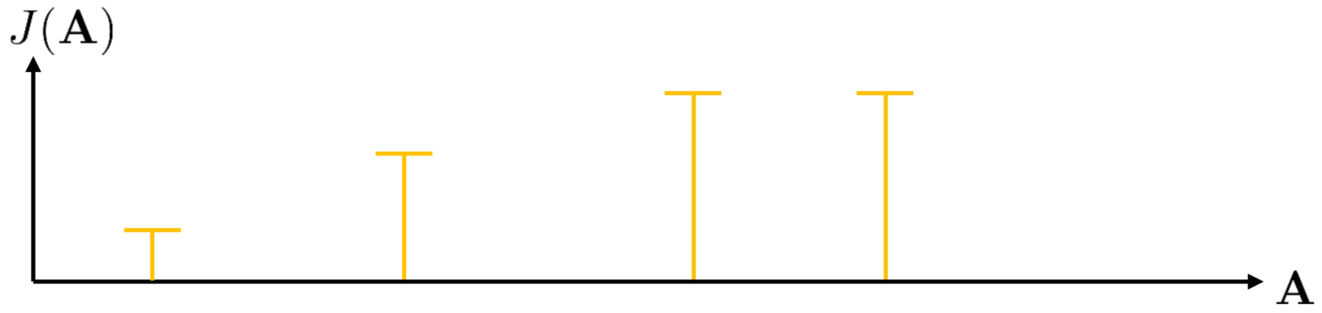

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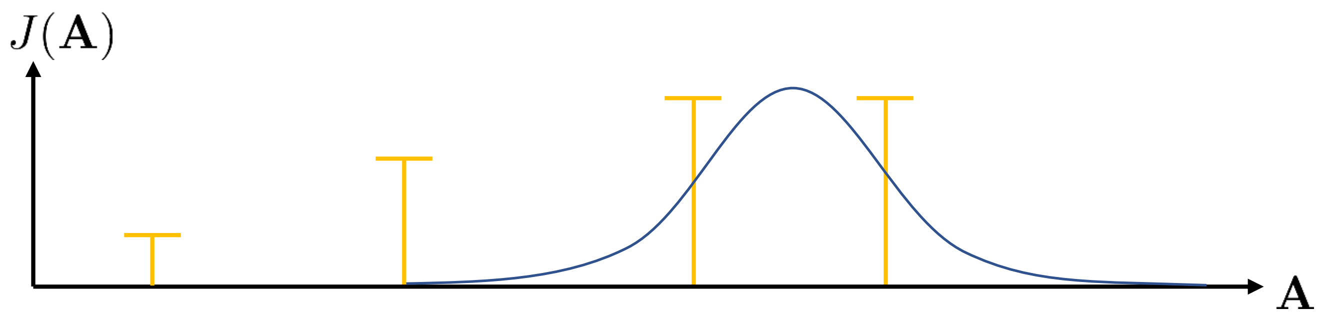

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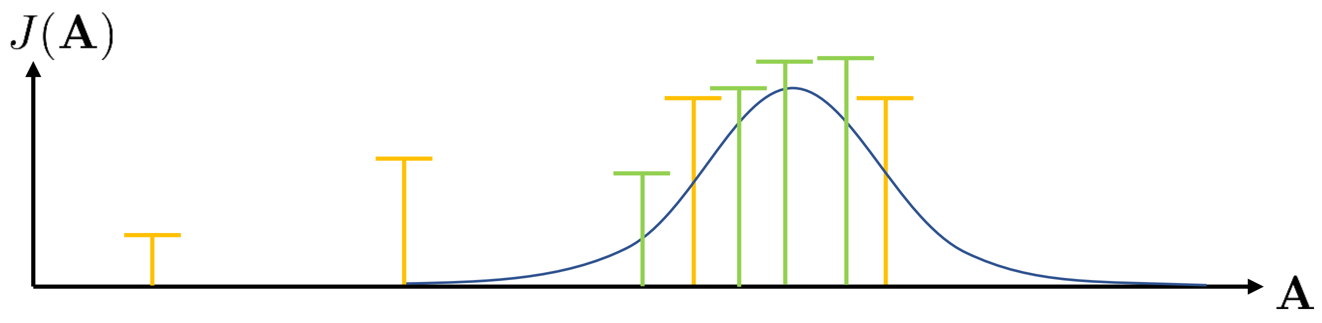

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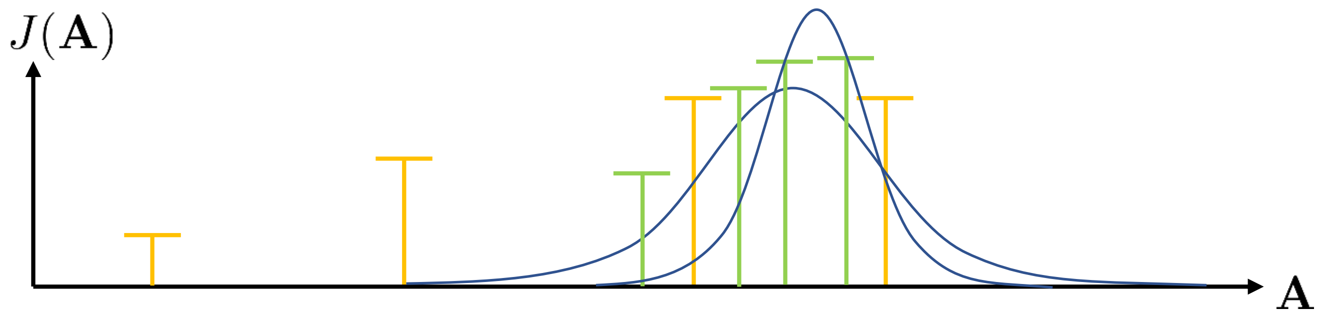

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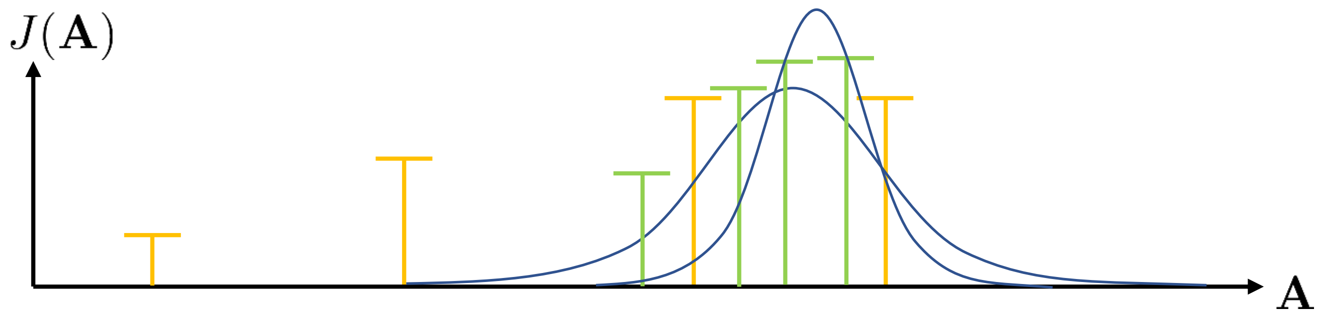

cross-entropy method with continuous-valued inputs:

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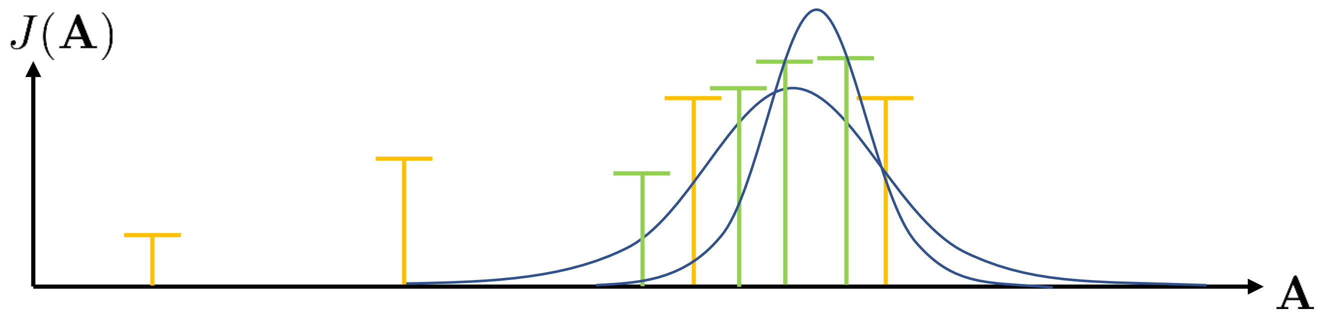

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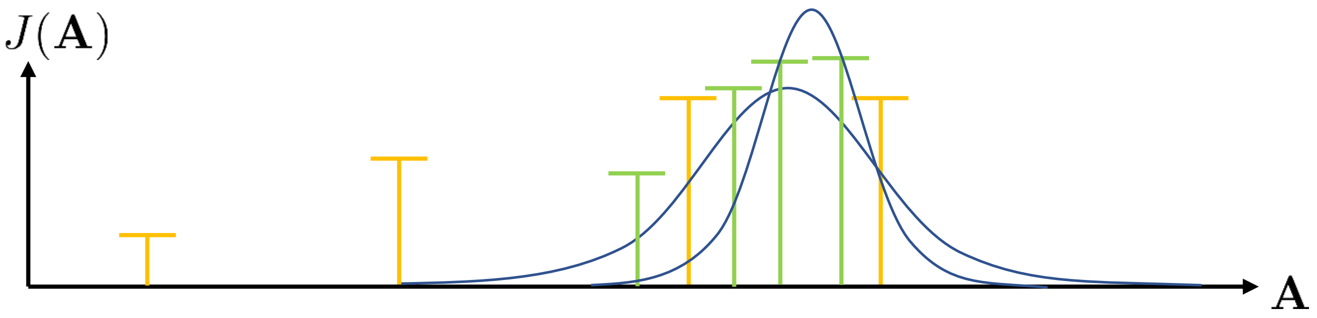

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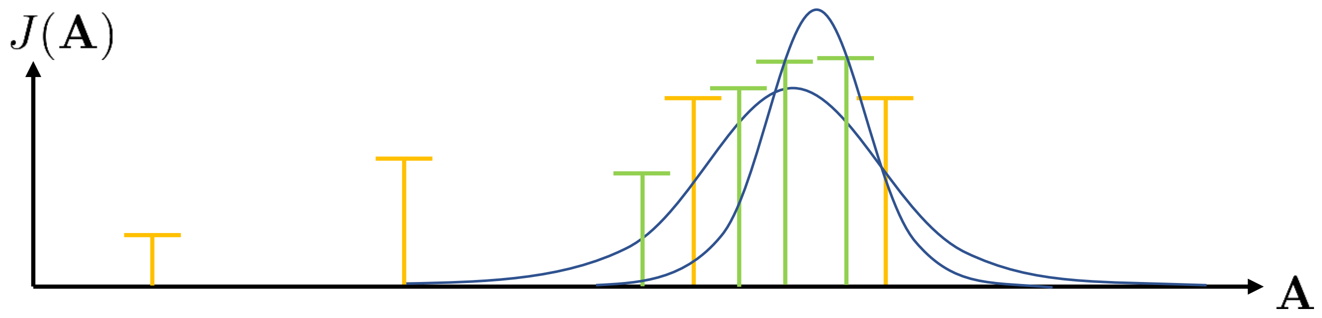

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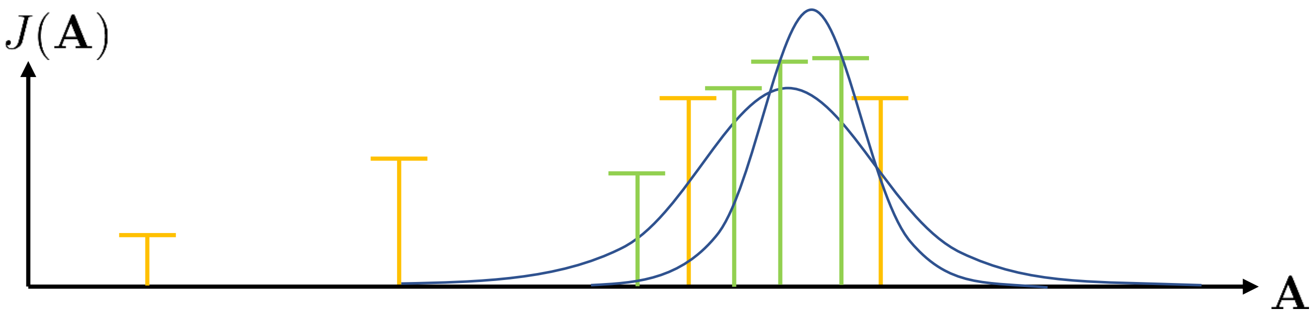

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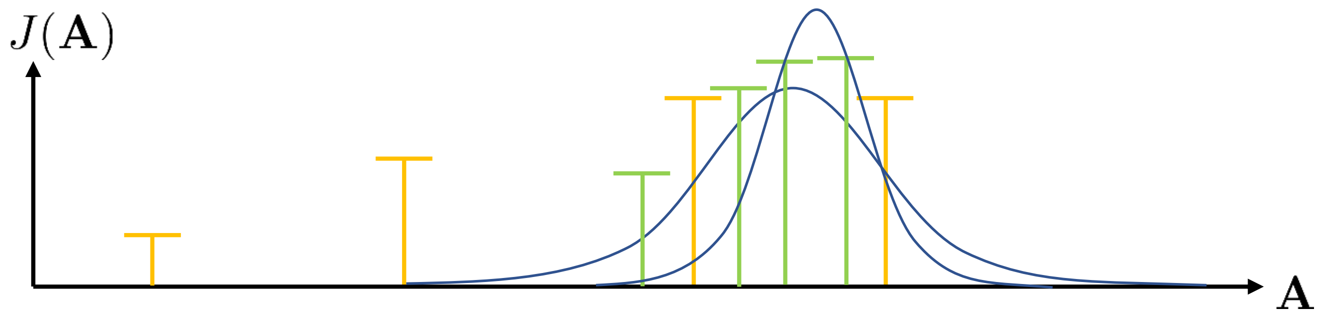

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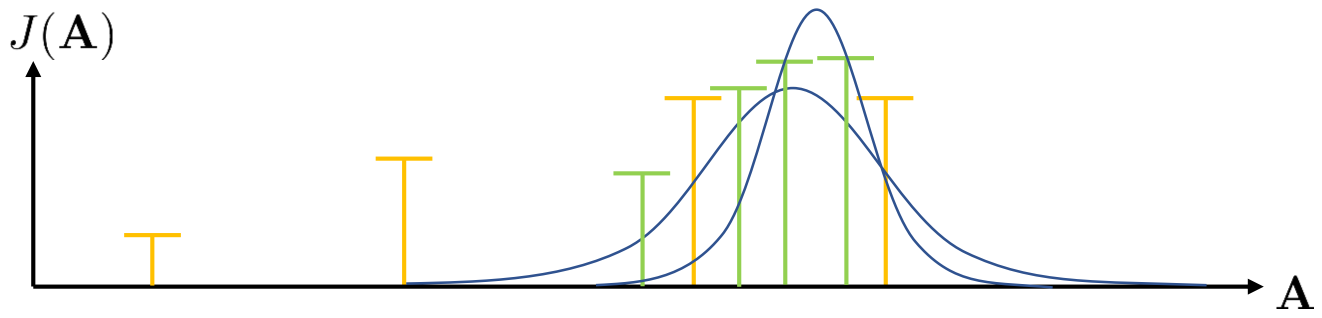

typically use Gaussian distribution

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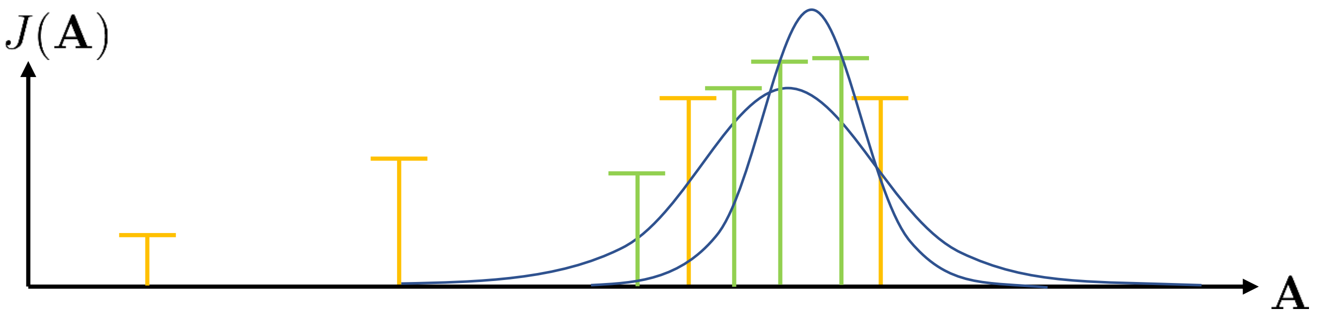

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see also: CMA-ES (sort of like CEM with momentum)

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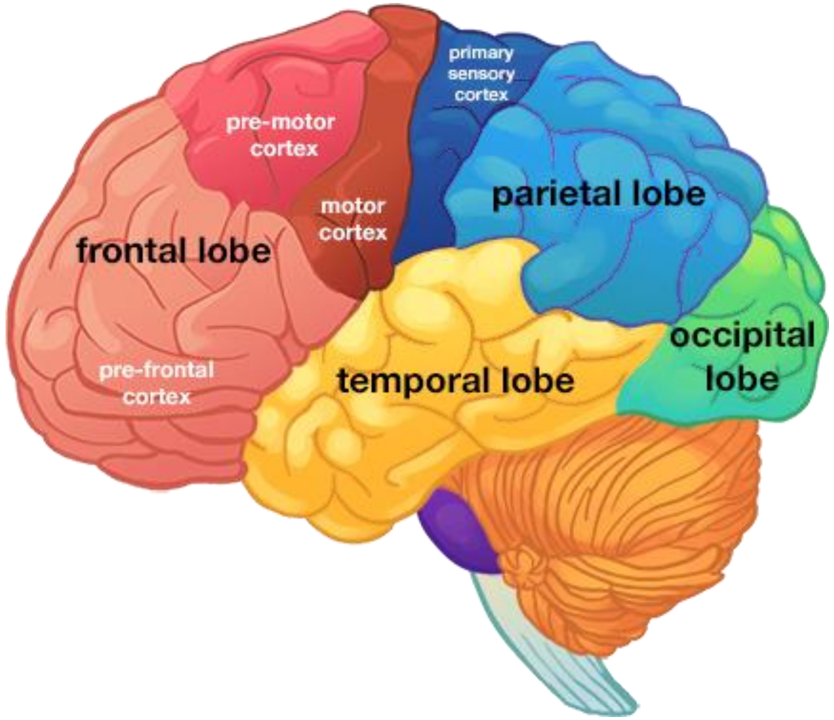
Imagination

s or $\phi(s)$, that is the question…

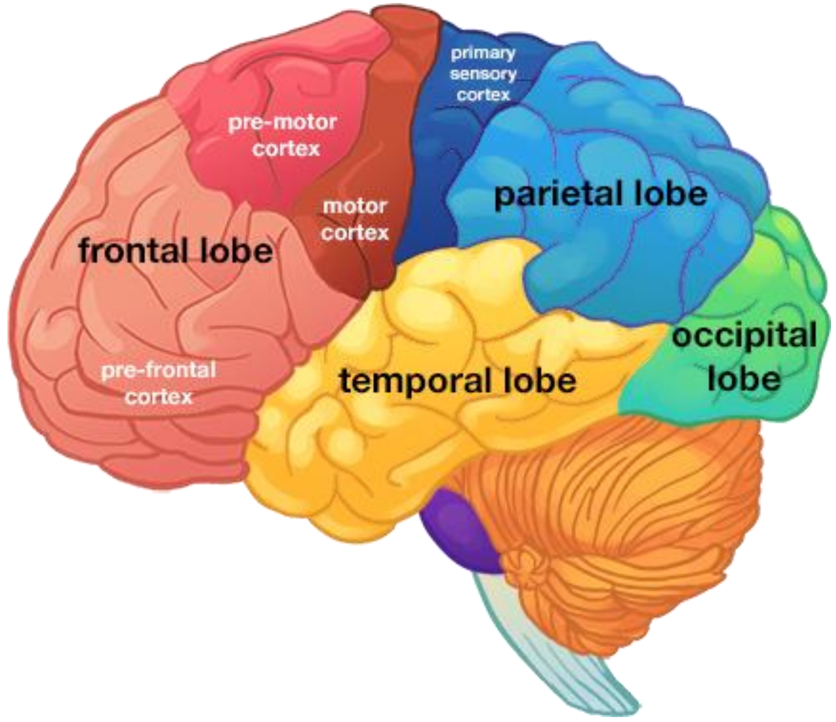
i.e. how important is it to have an accurate facsimile of the input images, vs and embedding tailored for planning?

Visual Imagination



Visual Imagination

What do people do?



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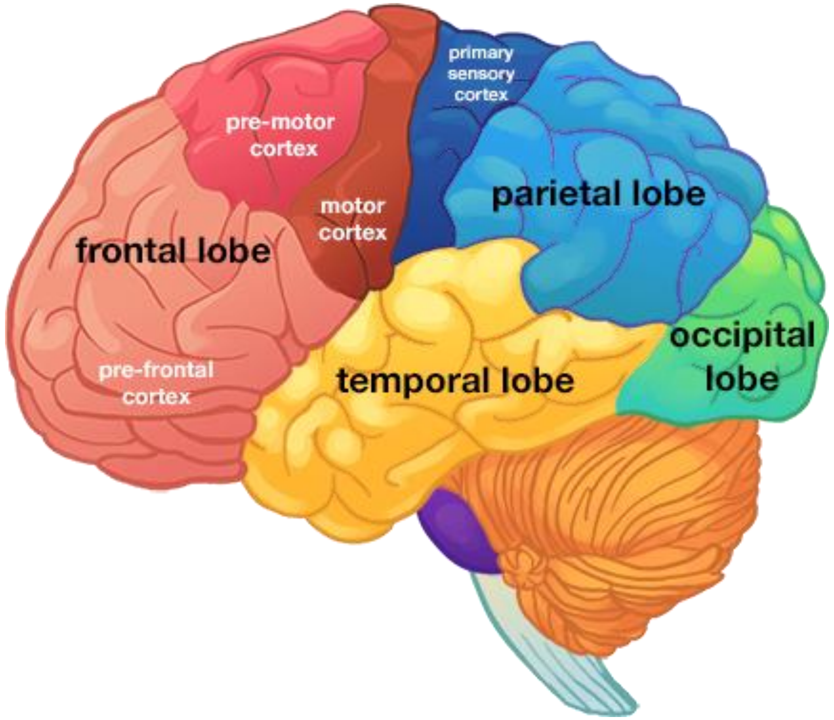
What do people do?

We know the occipital/temporal areas are involved (visual and planning).



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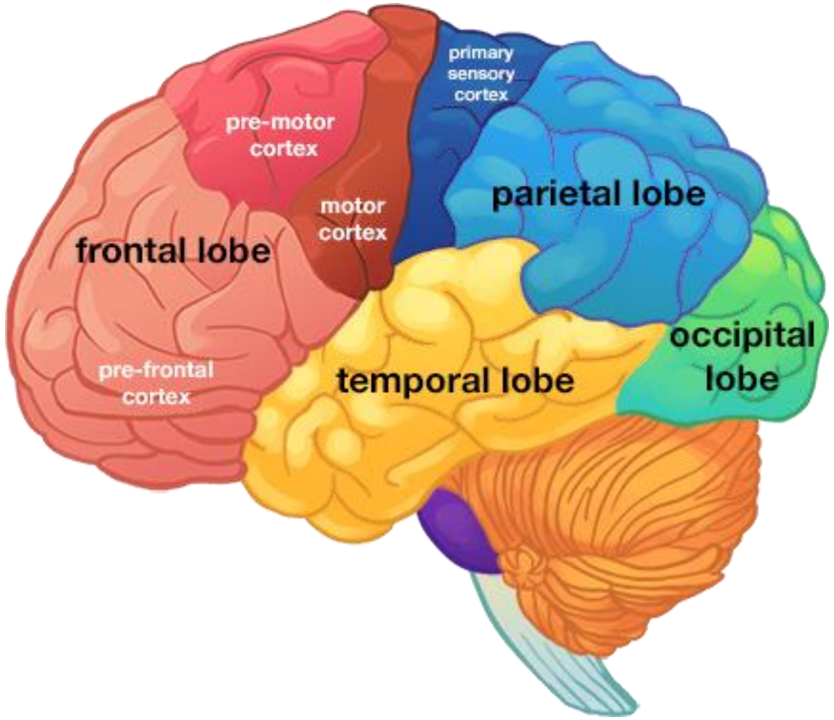
But the results on primary visual cortex V1 (the pixels) in visual imagination experiments is mixed.



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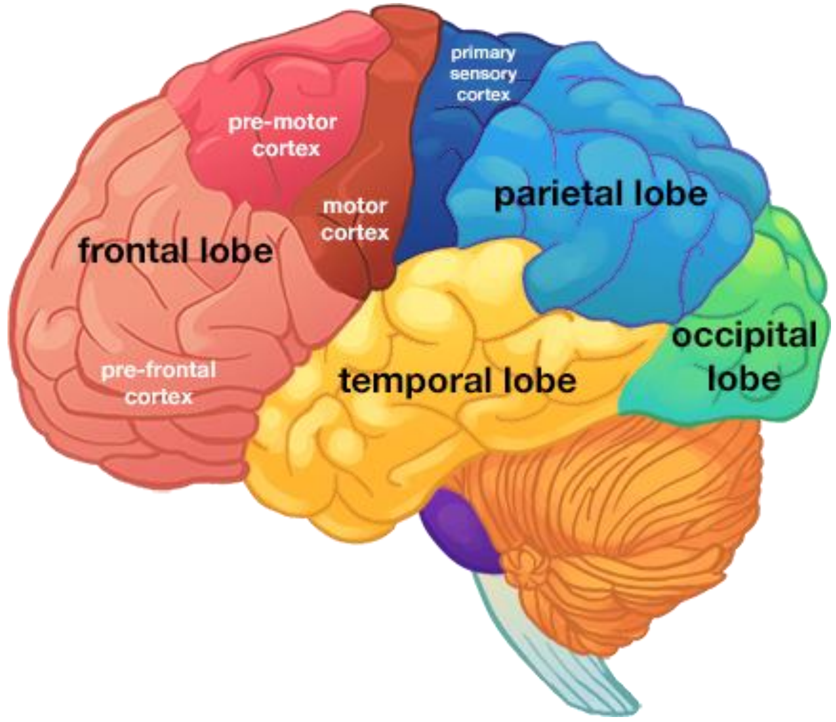

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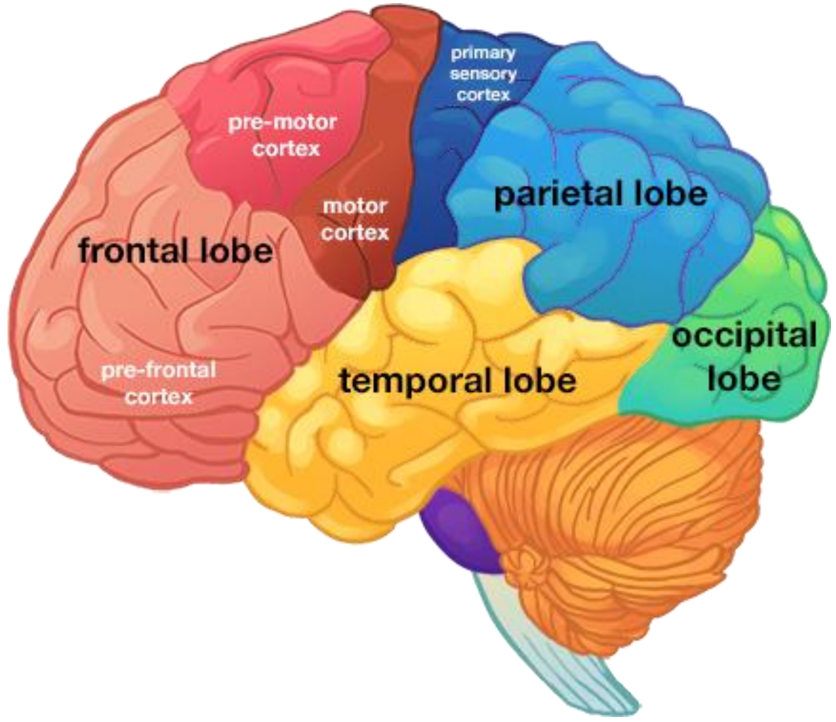
See this recent study:
"Vivid visual mental imagery in the absence of the primary visual cortex" by Bridge et al.



Imagination Architecture

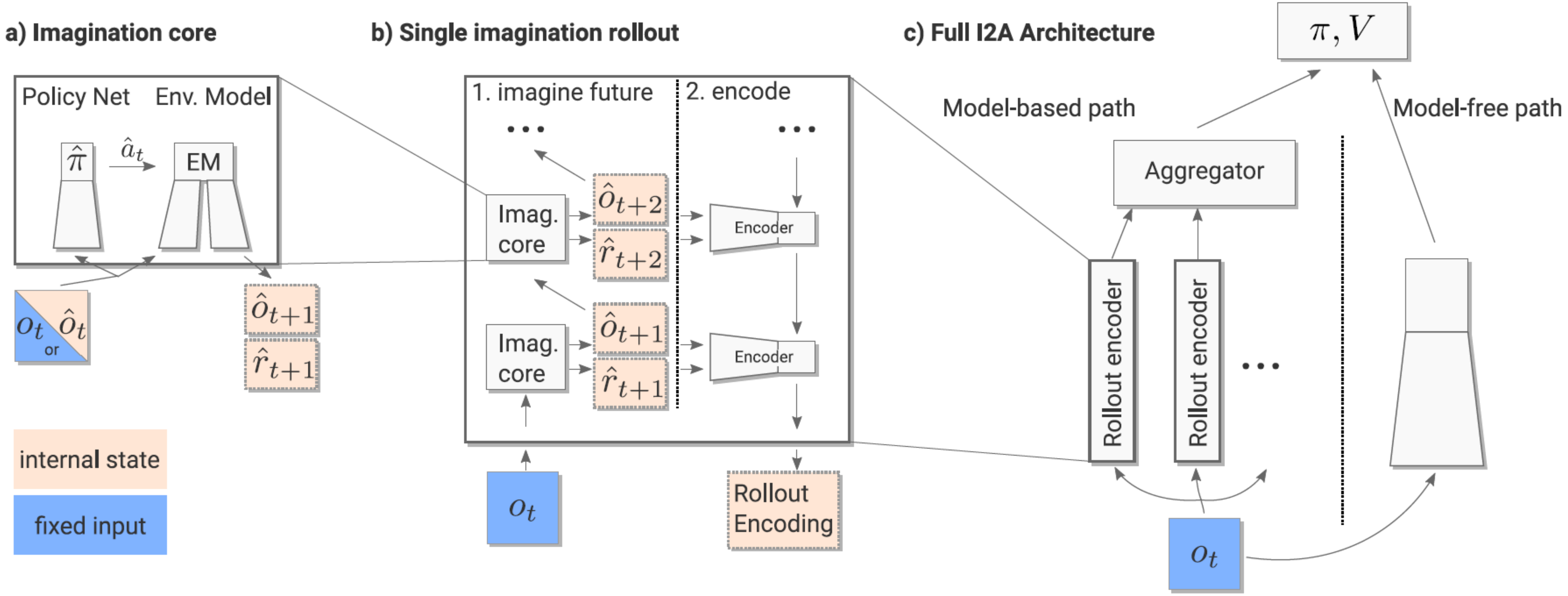
"Imagination-Augmented Agents for Deep Reinforcement Learning" Weber et al

In the mean time we can build it and try it…

Imagination Architecture

"Imagination-Augmented Agents for Deep Reinforcement Learning" Weber et al

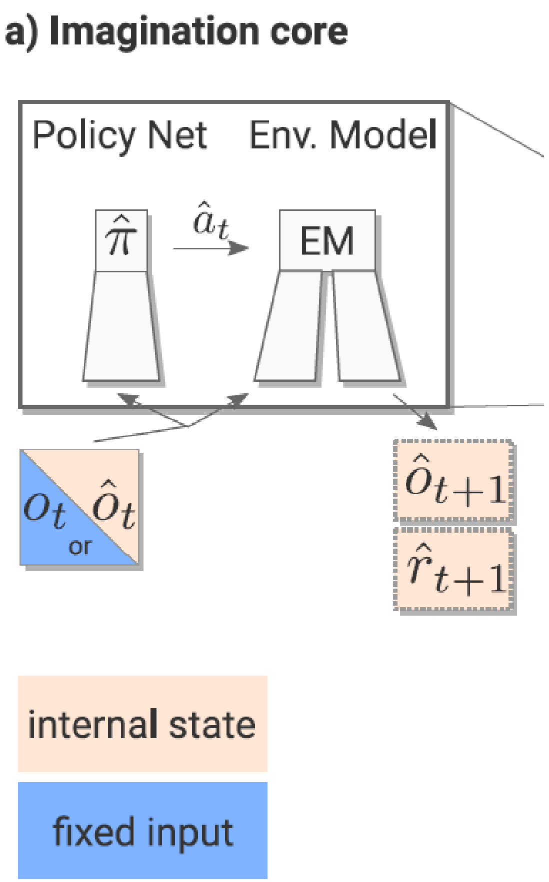
Symbols with $\hat{}$ represent imagined values



Imagination Architecture

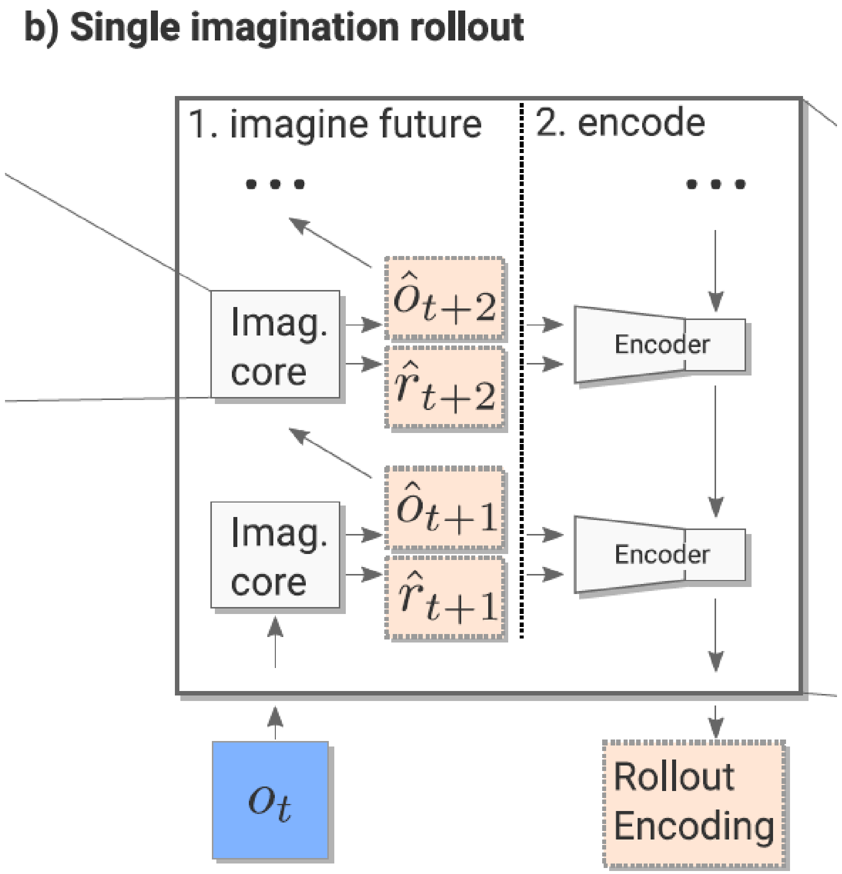
The rollout policy $\hat{\pi}$ generates the action sequence.

Its produced by a standard policy network.



Imagination Architecture

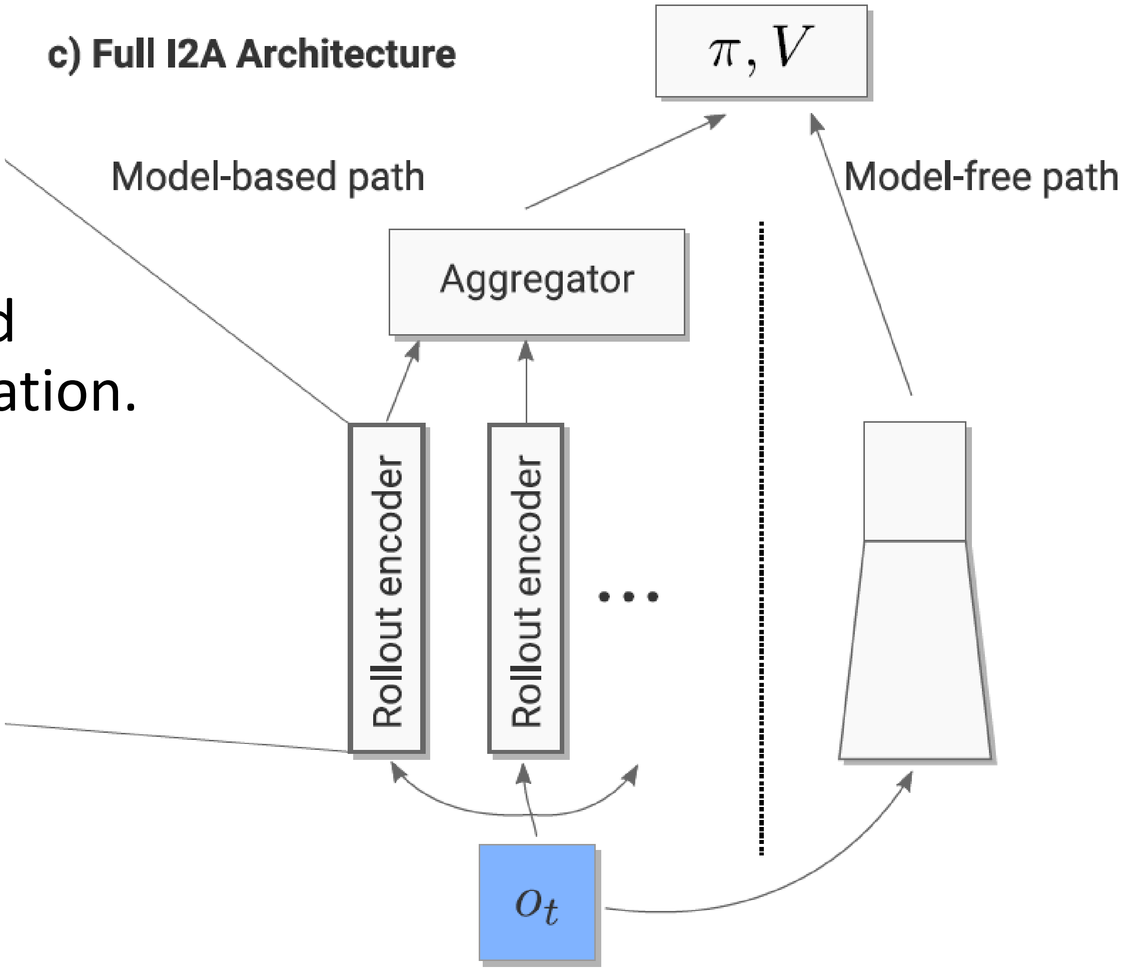
The imagination rollout block recurrently computes a sequence of observations and rewards.



Imagination Architecture

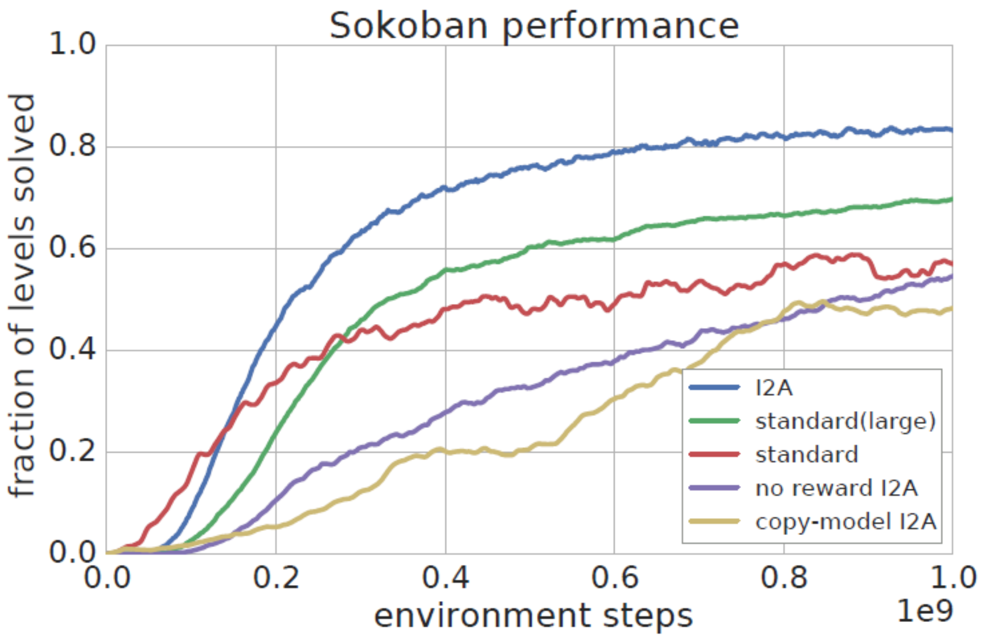
The imagined sequence forms “advice”
to the final policy and value function blocks.

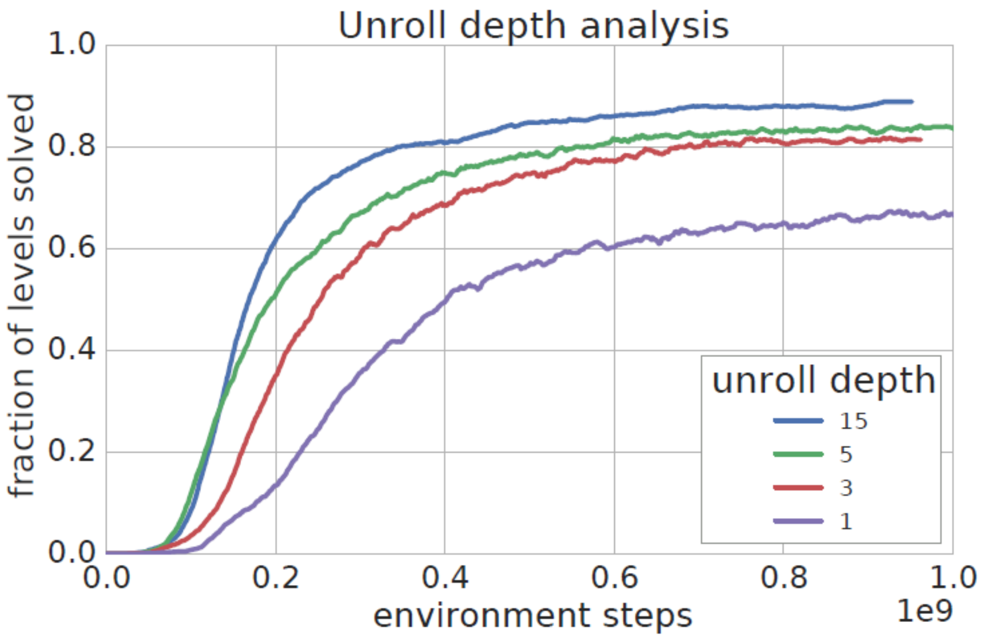
They are both also informed by a feed-forward
network connected to the current real observation.



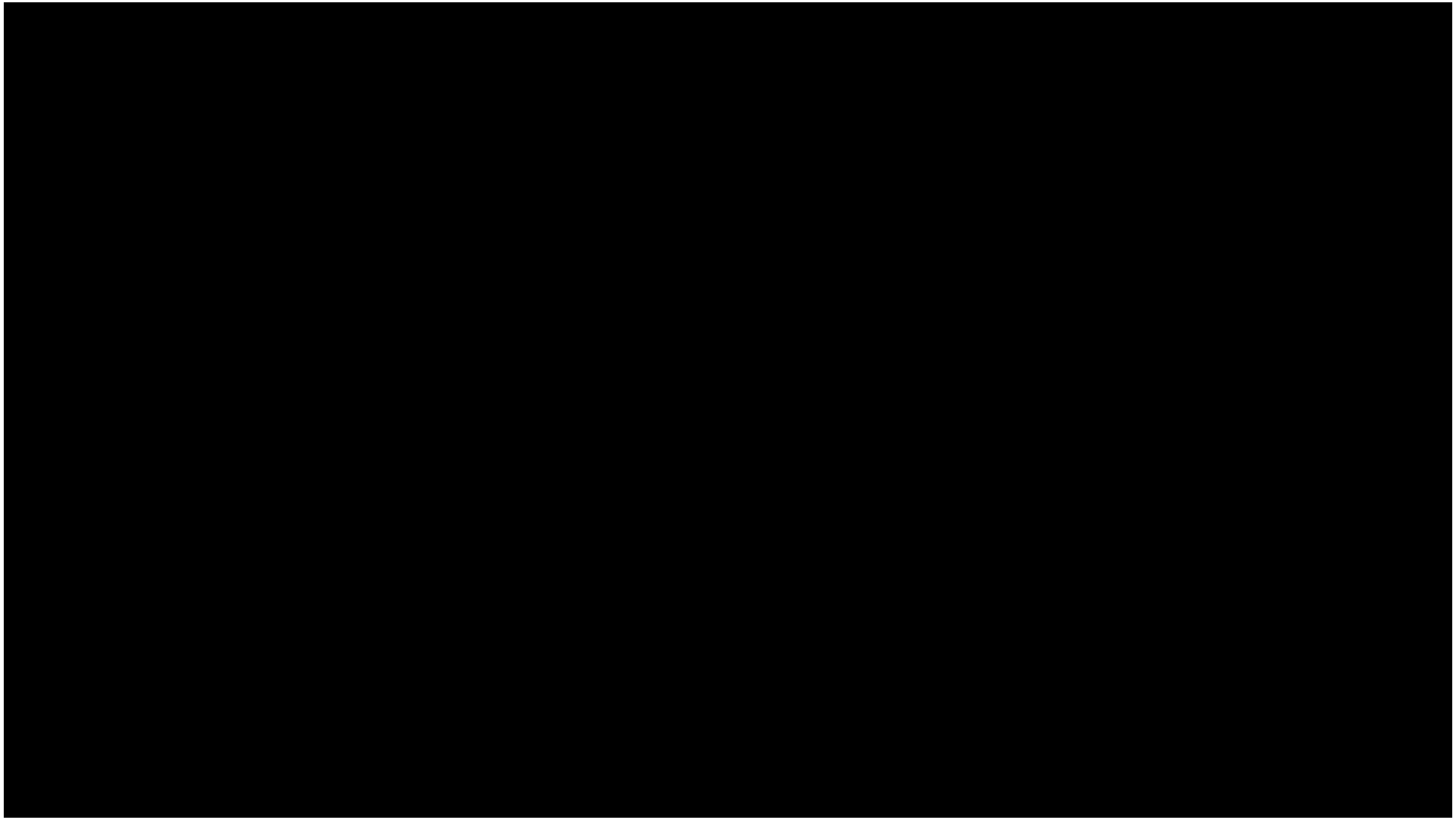
Imagination Architecture

Performance on Sokoban:



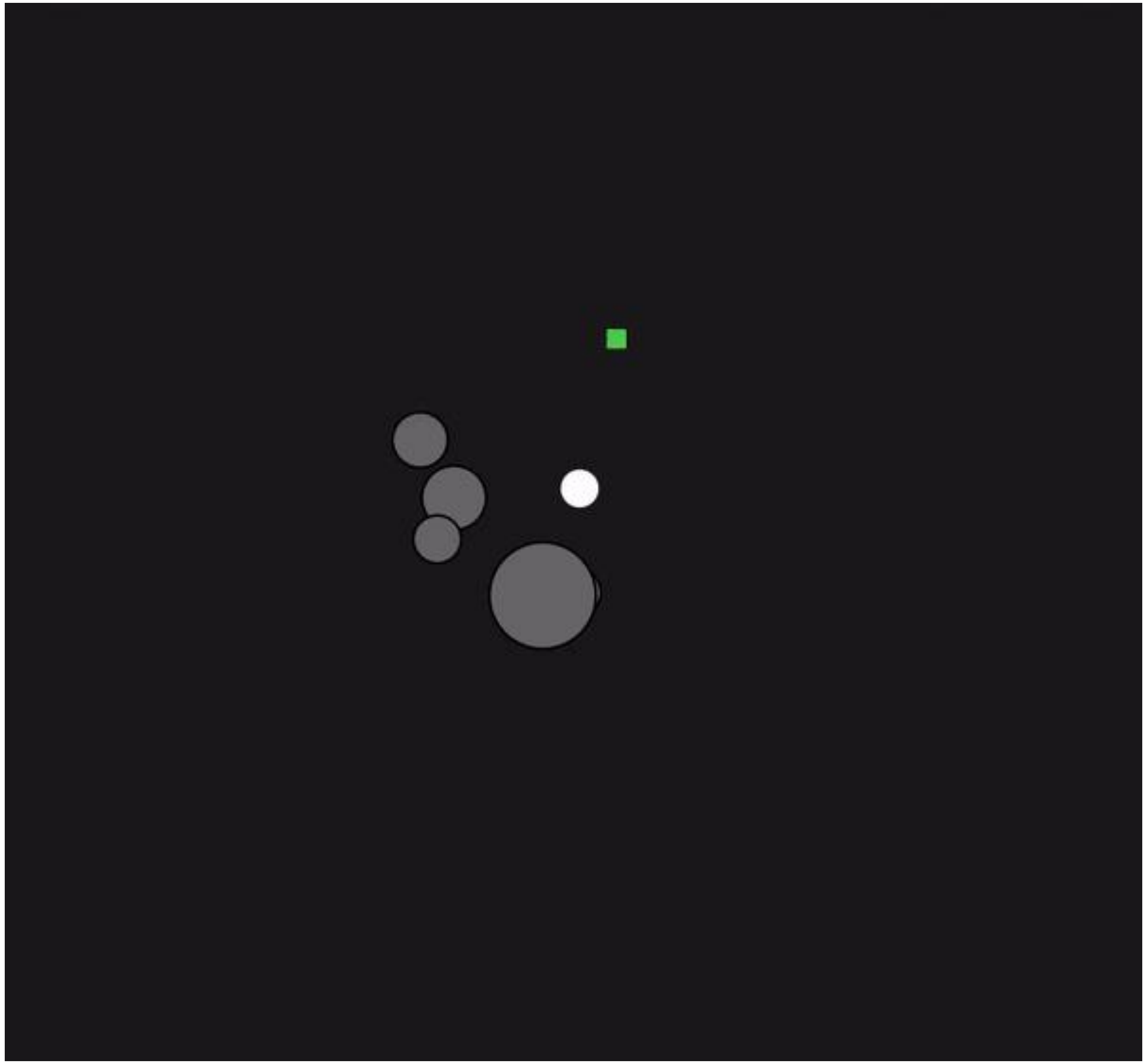


Imagination Architecture



Imagination Architecture

- An agent playing the spaceship game.
- Red lines are executed trajectories.
- Blue and green are imaged trajectories.



Take-aways

- Optimistic exploration methods favor poorly-explored states, assuming their value is as high as it could be. Use counts to estimate uncertainties.
- An elegant way to model θ uncertainty is to train an ensemble of models using bootstrap sampling. Sample from the posterior → choose a model.
- Avoid random walks at all costs! $\Omega(N^2)$ cost to explore N states. Simple methods: epsilon-greedy, entropy regularization and Thompson sampling all do random walks.
- Doing better requires memory (counts, environment models etc.)

Take-aways

- Can plan and anticipate states and rewards with a simplified environment model ($\phi(s)$ instead of s).
- Human visual imagination doesn’t always use pixel-level representation.
- But visual representation is the most powerful, and allows the system to use policies or other networks trained for very different tasks.
- Imagination was used as “advice” in the imagination architecture. Another network needs to learn how to use it (CEM etc.).