Carnegie Mellon

School of Computer Science

Deep Reinforcement Learning and Control

Exploration by Curiosity and External Memory

Fall 2021, CMU 10-703

Instructors
Katerina Fragkiadaki
Russ Salakhutdinov

Exploration: It’s all about modeling our uncertainty

- Exploration: trying out new things (new behaviours), with the hope of discovering higher rewards
- Exploitation: doing what **you know so far** will yield the highest reward

Exploration with ϵ — greedy

- Are we exploring by adding random noise to our actions?
- Imagine what would happen if you go to a new museum and you try to explore its exhibits. What would be your strategy for efficient exploration?

Exploration is all you need: no reward RL

- Exploration: trying out new things (new behaviors), with the hope of discovering higher rewards
- We explore efficiently once **we know what we do not know,** and target our exploration to the unknown part of the space.
- My goal is to maximize my learning progress, i.e., learn most about the world

Motivation

Motivation: “Forces” that energize an organism to act and that direct its activity

- Extrinsic Motivation: being moved to do something because of some external reward ($$, a prize, etc.).
    - Problem: such rewards are sparse..
- Intrinsic Motivation: being moved to do something because it is inherently enjoyable (curiosity, exploration, novelty, surprise, incongruity, complexity…)
    - Gain: Task independent! Free of human supervision, no need to code up reward functions to incentivize the agent. A general loss functions that drives learning.

Curiosity VS Survival

> “As knowledge accumulated about the conditions that govern exploratory behavior and about how quickly it appears after birth, it seemed less and *less likely that this behavior could be a derivative of hunger, thirst, sexual appetite, pain, fear of pain, and the like*, or that stimuli sought through exploration are welcomed because they have previously accompanied satisfaction of these drives.”
>
> D. E. Berlyne, *Curiosity and Exploration*, Science, 1966

Intrinsic Motivation different than Intrinsic Necessity: being moved to do something because it is necessary (eat, drink, find shelter from rain…)

Curiosity and Never-ending Learning

Why should we care?

- Because curiosity is a general, task-independent cost function, that if we successfully incorporate to our learning machines, it may result in agents that (want to) improve with experience, like people do.
- Those intelligent agents would not require supervision by coding up reward functions for every little task, they would learn (almost) autonomously
- Curiosity-driven motivation is beyond satisfaction of hunger, thirst, and other biological activities (which arguably would be harder to code up in artificial agents..)

Curiosity-driven exploration

Seek **novelty/surprise**:

- Visit *novel states* s
- Observe *novel state transitions* $(s, a) \rightarrow s'$

Q: How can we computationally formalize that?
A: Many answers provided in this lecture

Curiosity-driven exploration

- Ensembles of Q functions: modeling uncertainty of Q values
- State counting: the lower the count of the state the higher the exploration bonus
- Model prediction error: the higher the prediction error the higher the curiosity
- Reachability: the least reachable a state from a set of already reached states in my memory, the higher the exploration bonus
- Non-parametric memory of states and their transitions (reachability) of one to the other. Explore by maximizing coverage.

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We will be using a standard model-free or model-based RL method and add exploration-based rewards in addition to the external environment rewards

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We will use the non-parametric model of the environment that we built to win the hardest RL environment, simply by methodic exploration: remembering where I have been and searching further towards places I have not been.

Uncertainty-driven exploration

- Ensembles of Q functions: modeling uncertainty of Q values
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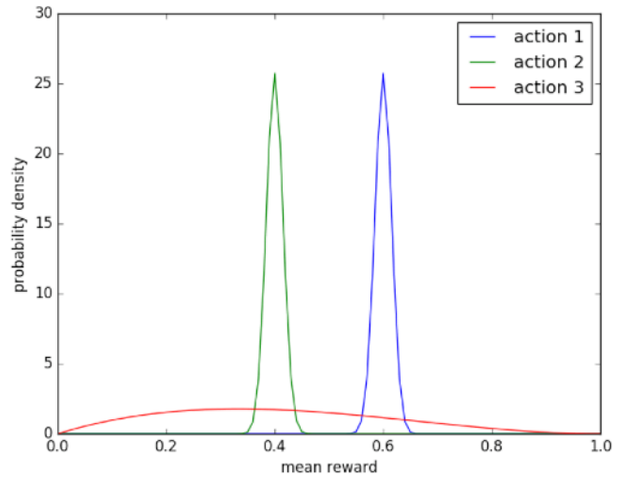
Exploration in Bandits

Thompson Sampling

Represent a **posterior distribution** of mean rewards of the arms, as opposed to **point estimates**.



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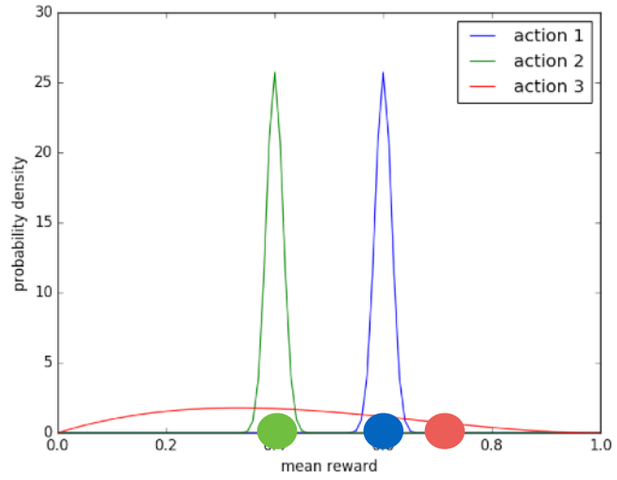
1. Sample from it: $\theta_1, \theta_2, \cdots, \theta_k \sim \hat{p}(\theta_1, \theta_2 \cdots \theta_k)$



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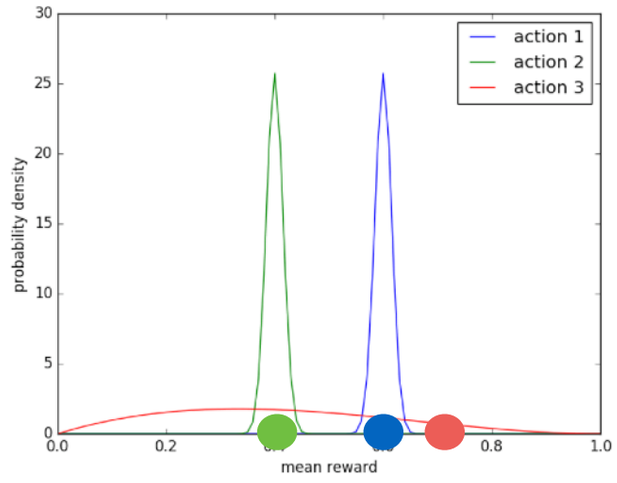

1. Sample from it: $\theta_1, \theta_2, \cdots, \theta_k \sim \hat{p}(\theta_1, \theta_2 \cdots \theta_k)$
2. Choose action: $a = \arg\max_a \mathbb{E}_\theta[r(a)]$

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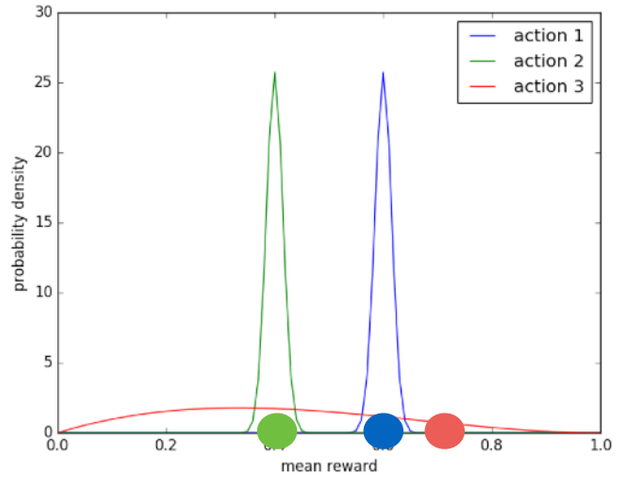

Play the red arm!

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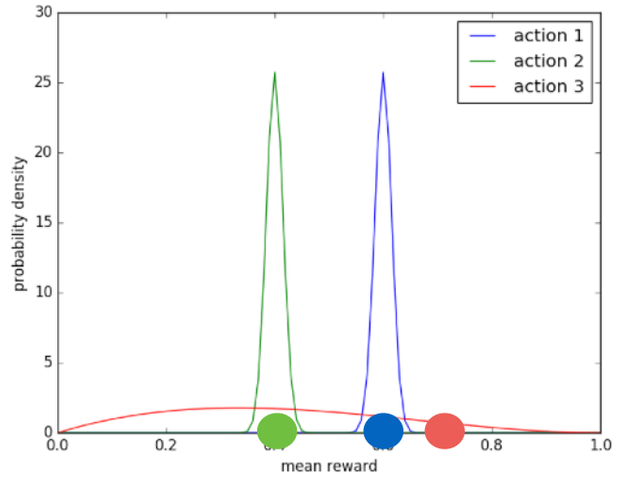
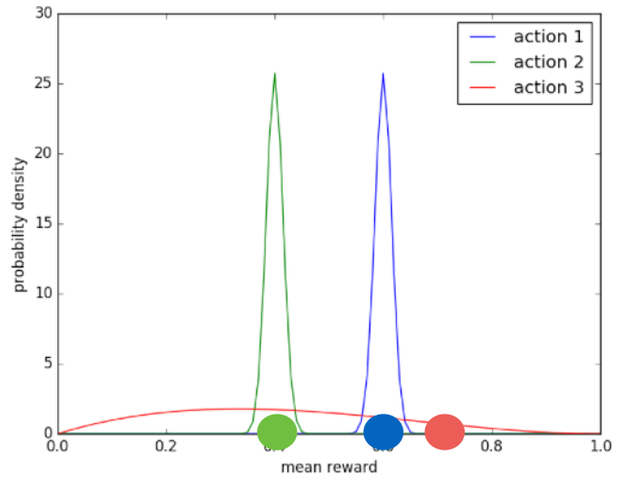


0.8!

Exploration in Bandits

Thompson Sampling



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2. Choose action: $a = \arg\max_a \mathbb{E}_\theta[r(a)]$
3. Play action, observe reward
4. Update the mean reward distribution

- Can I do something like that for general MDPs?
- What is the equivalent of mean rewards for geenral MDP?

Exploration via Posterior Sampling of Q functions

Represent a posterior distribution of Q functions, instead of a point estimate.

1. Sample from $P(Q)$: $Q \sim P(Q)$
2. Choose actions according to this Q for one episode:

$$a = \arg\max_a Q(a, s)$$

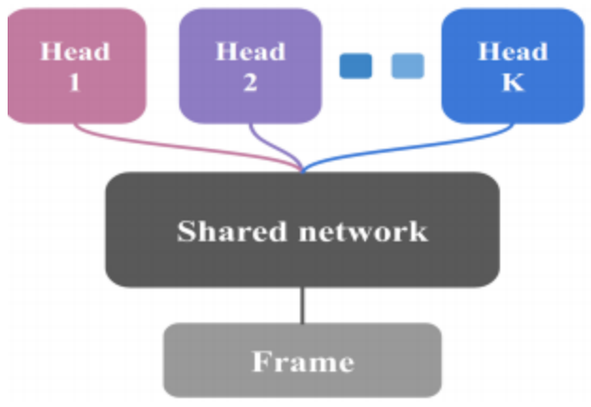
3. Update the Q distribution using the collected experience tuples

Then we do not need ϵ-greedy for exploration! Better exploration by representing uncertainty over Q.

But how can we learn a distribution of Q functions $P(Q)$ if Q function is a deep neural network?

Exploration via Posterior Sampling of Q-functions

1. **Bayesian neural networks**. Estimate posteriors for the neural weights, as opposed to point estimates. We just saw that..
2. **Neural network ensembles.** Train multiple Q-function approximations each on using different subset of the data. A reasonable approximation to 1.
3. **Neural network ensembles with shared backbone**. Only the heads are trained with different subset of the data. A reasonable approximation to 2 with less computation.



4. **Ensembling by dropout.** Randomly mask-out (zero out)neural network weights, to create different neural nets, both at train and test time. reasonable approximation to 2.

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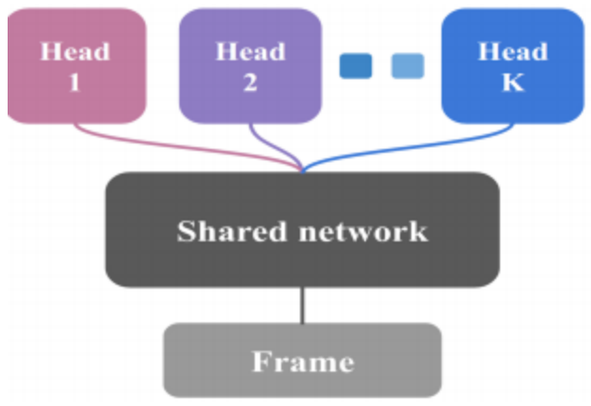

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Deep exploration with bootstrapped DQN, *Osband et al.*

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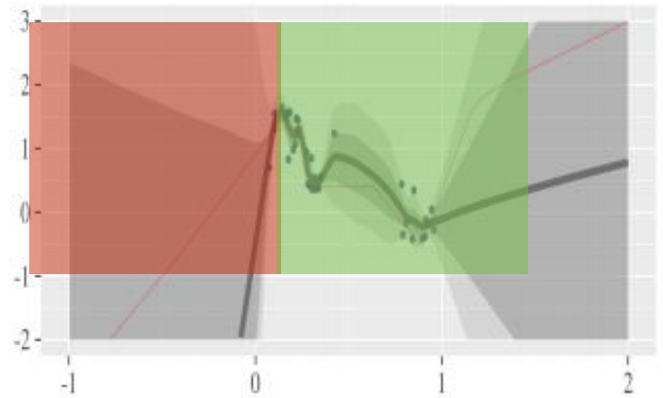
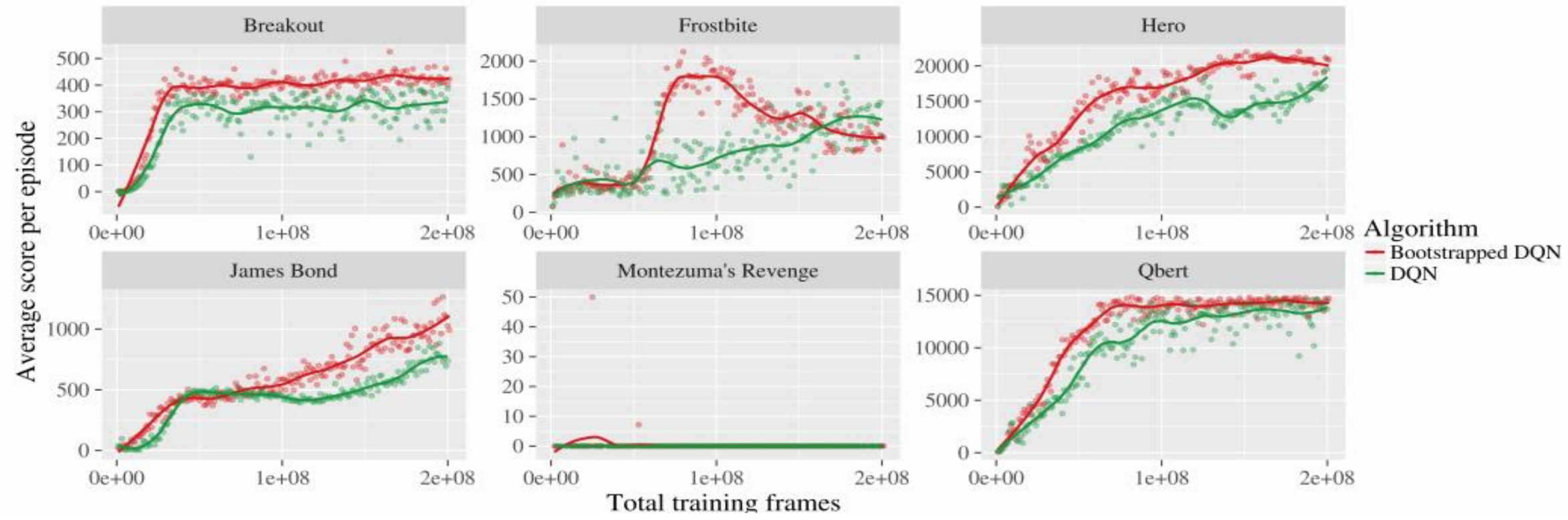


With ensembles we achieve similar things as with Bayesian nets:

- The entropy of predictions of the network (obtained by sampling different heads) is high in the no data regime. Thus, Q function values will have high entropy there and encourage exploration.
- When Q values have low entropy, i exploit, i do not explore.

Deep exploration with bootstrapped DQN, *Osband et al.*

Exploration via Posterior Sampling of Q-functions



Deep exploration with bootstrapped DQN, *Osband et al.*

Curiosity-driven exploration-one way to do it

We will add exploration reward bonuses to the extrinsic (task-related) rewards:

Independent of the task in hand!

$$R^t(s,a,s') = \underbrace{r(s,a,s')}_{extrinsic} + \underbrace{\mathcal{B}^t(s,a,s')}_{intrinsic}$$

We would then be using rewards $R^t(s,a,s')$ in our favorite RL method.

Curiosity-driven exploration-one way to do it

We will add exploration reward bonuses to the extrinsic (task-related) rewards in our favorite model free RL method.

Independent of the task in hand

$$R^t(s,a,s') = \underbrace{r(s,a,s')}_{extrinsic} + \underbrace{\mathcal{B}^t(s,a,s')}_{intrinsic}$$

Exploration reward bonuses are non stationary: as the agent interacts with the environment, what is now new and novel, becomes old and known.

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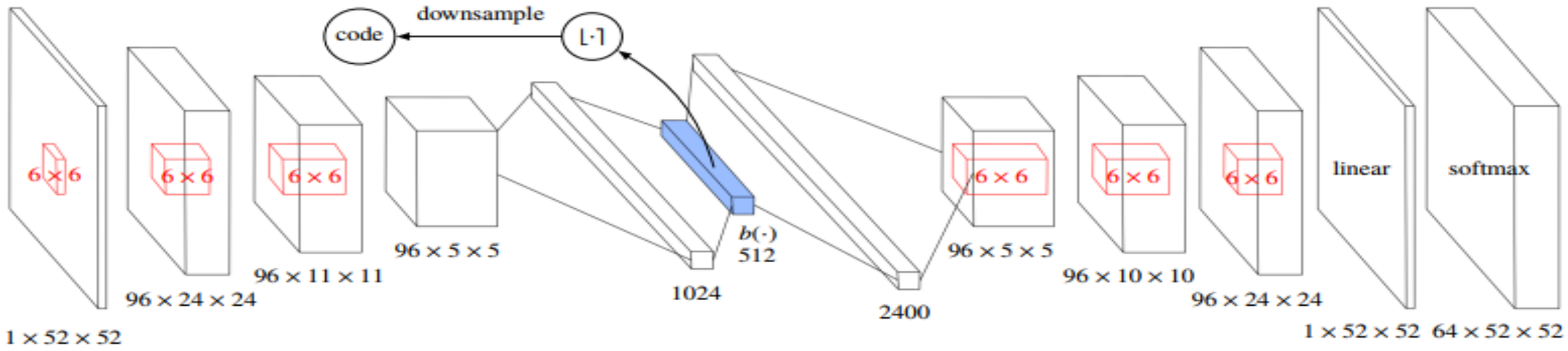
State Counting with DeepHashing

- We count states (images) but not in pixel space, but in latent compressed space.
- Compress s into a latent code, then count occurrences of the code.
- How do we get the image encoding? E.g, using autoencoders.

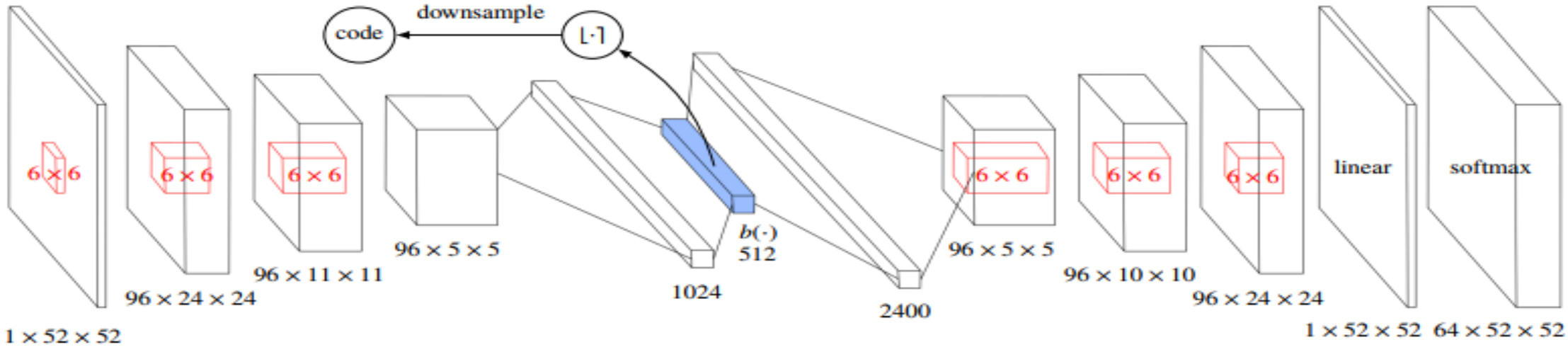


- Note: There is no guarantee such reconstruction loss will capture the important things that make two states to be similar or not policy wise..

Exploration- A Study of Count-Based Exploration for Deep Reinforcement Learning, *Tang et al.*

Exploration rewards

Add exploration reward bonuses that encourage policies to visit states with smaller counts:



$$R^t(s, a, s') = \underbrace{r(s, a, s')}_{\text{extrinsic}} + \underbrace{\mathcal{B}^t(\phi(s))}_{\text{intrinsic}}$$

State Counting with DeepHash

- We still count states (images) but not in pixel space, but in latent compressed space.
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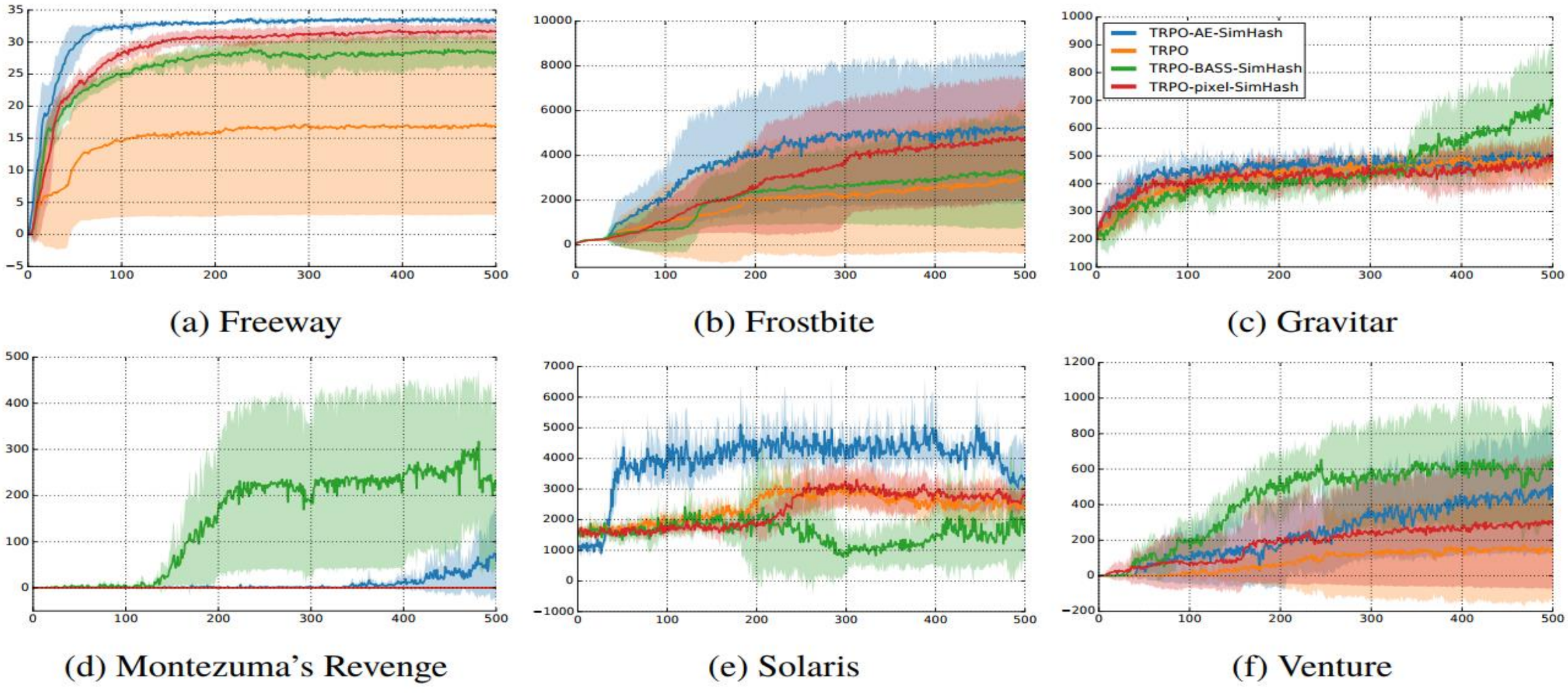

(a) Freeway (b) Frostbite (c) Gravitar

(d) Montezuma's Revenge (e) Solaris (f) Venture

Exploration- A Study of Count-Based Exploration for Deep Reinforcement Learning, *Tang et al.*

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Exploration rewards

Add exploration reward bonuses that encourage policies to visit states that will cause the prediction model to fail.

model error!

$$R^t(s,a,s') = \underbrace{r(s,a,s')}_{\text{extrinsic}} + \underbrace{\mathscr{B}^t(\|T(s,a;\theta) - s'\|)}_{\text{intrinsic}}$$

Note: we will be using $T(s, a; \theta)$ to denote the dynamics (transition) function.

Computational Curiosity

- “The direct goal of curiosity and boredom is to improve the **world model**. The indirect goal is to ease the learning of new goal-directed action sequences.”
- “The same complex mechanism which is used for ‘normal’ goal-directed learning is used for implementing curiosity and boredom. There is no need for devising a separate system which aims at improving the world model.”
- “Curiosity Unit”: reward is a function of the mismatch between model’s current predictions and actuality. There is positive reinforcement whenever the system fails to correctly predict the environment.
- “Thus the usual credit assignment process ... encourages certain past actions in order to repeat situations similar to the mismatch situation.” (planning to make your (internal) world model to fail)

Jurgen Schmidhuber, 1991, 1991, 1997

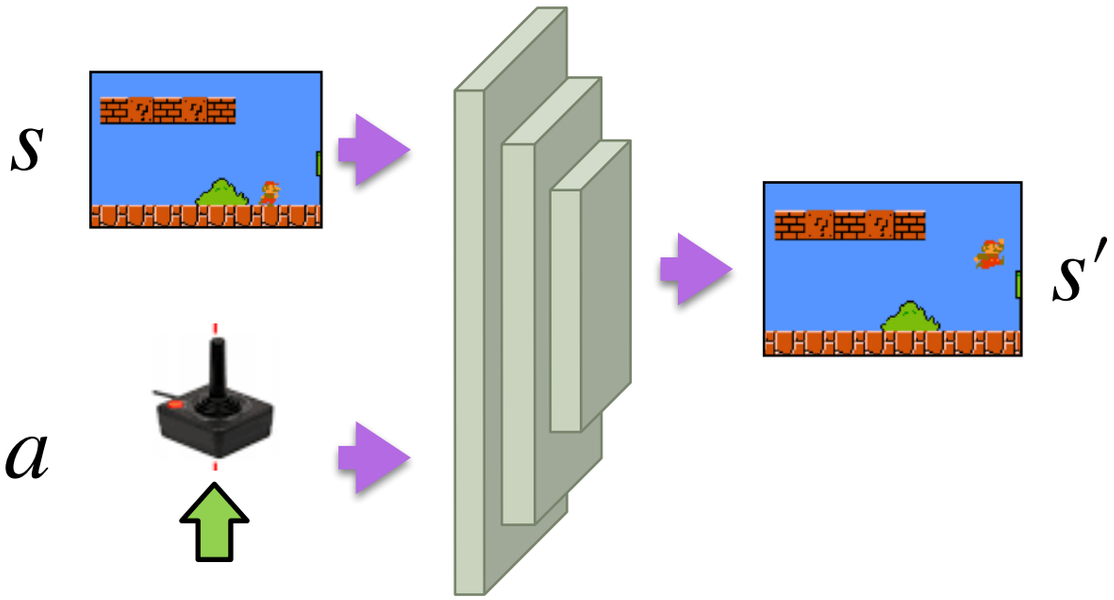
Computational Curiosity

In other words:

- Model learning and model improvement can be cast as the goals of goal-seeking behaviour.
- My goal is not to beat Atari but to improve my Atari model.
- OK. What is my reward then that trying to maximize that reward will lead to fast model learning?

Learning Visual Dynamics

Exploration reward bonus $\mathscr{B}^t(s, a, s') = \|\mathrm{T}(s, a; \theta) - s'\|$



$$\min_{\theta} . \quad \|\mathrm{T}(s, a; \theta) - s'\|$$

Here we predict the visual observation!

$$R^t(s, a, s') = \underbrace{r(s, a, s')}_{\text{extrinsic}} + \underbrace{\mathscr{B}^t(s, a, s')}_{\text{intrinsic}}$$

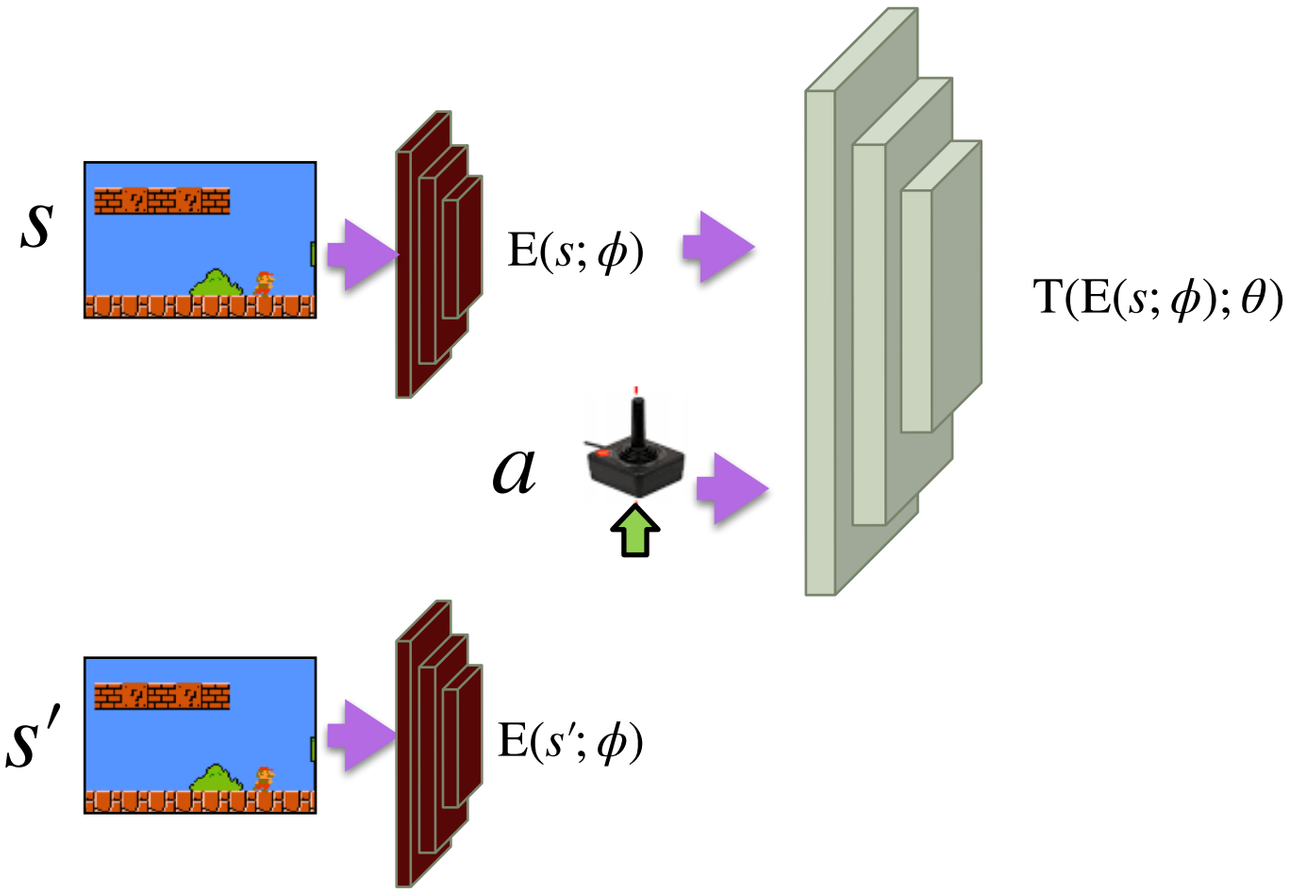
Predicting Raw Sensory Input (Pixels)

Should our prediction model be predicting the input observations?

- Observation prediction is difficult especially for high dimensional observations.
- Observation contains a lot of information unnecessary for planning, e.g., dynamically changing backgrounds that the agent cannot control and/or are irrelevant to the reward.

Learning Visual Dynamics

Exploration reward bonus $\mathcal{B}^t(s, a, s') = \|\mathrm{T}(\mathrm{E}(s;\phi), a;\theta) - \mathrm{E}(s';\phi)\|$



$$\min_{\theta,\phi} . \quad \|\mathrm{T}(\mathrm{E}(s;\phi), a;\theta) - \mathrm{E}(s';\phi)\|$$

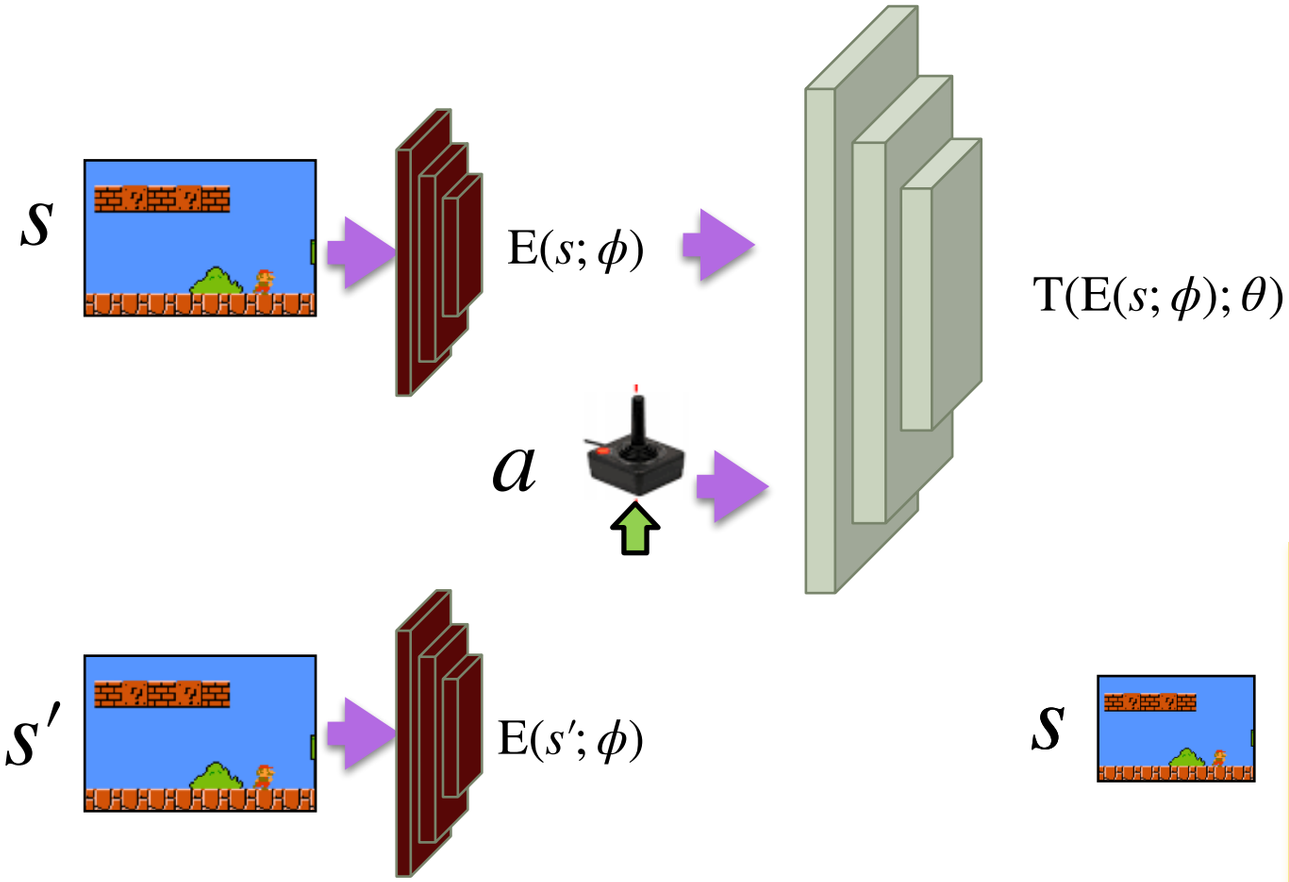
What is the problem with this optimization problem?

There is a trivial solution :-(

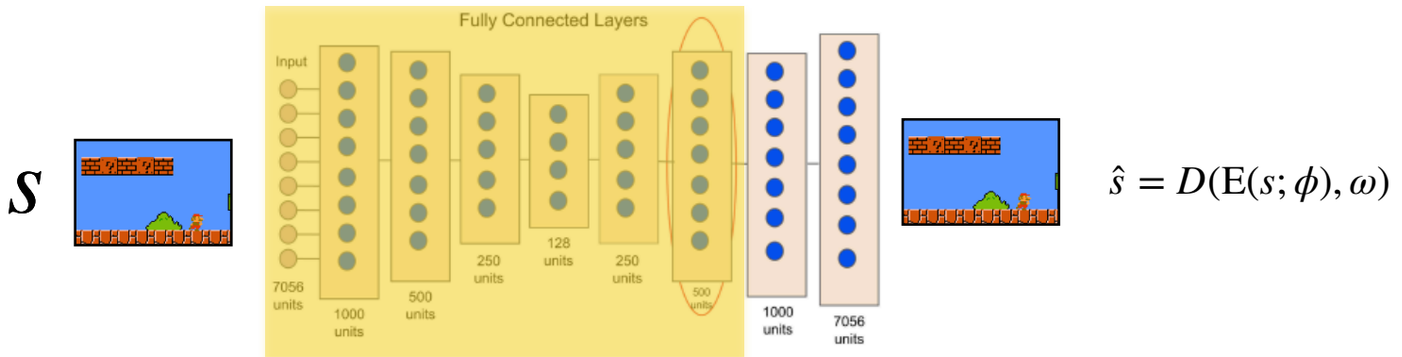
Learning Visual Dynamics

Exploration reward bonus $\mathcal{B}^t(s, a, s') = \|\mathrm{T}(\mathrm{E}(s;\phi), a; \theta) - \mathrm{E}(s';\phi)\|$

$$\min_{\theta} . \quad \|\mathrm{T}(\mathrm{E}(s;\phi), a; \theta) - \mathrm{E}(s';\phi)\|$$



Autoencoding loss: $\min_{\phi} . \quad \|D(\mathrm{E}(s;\phi), \omega) - s\|$

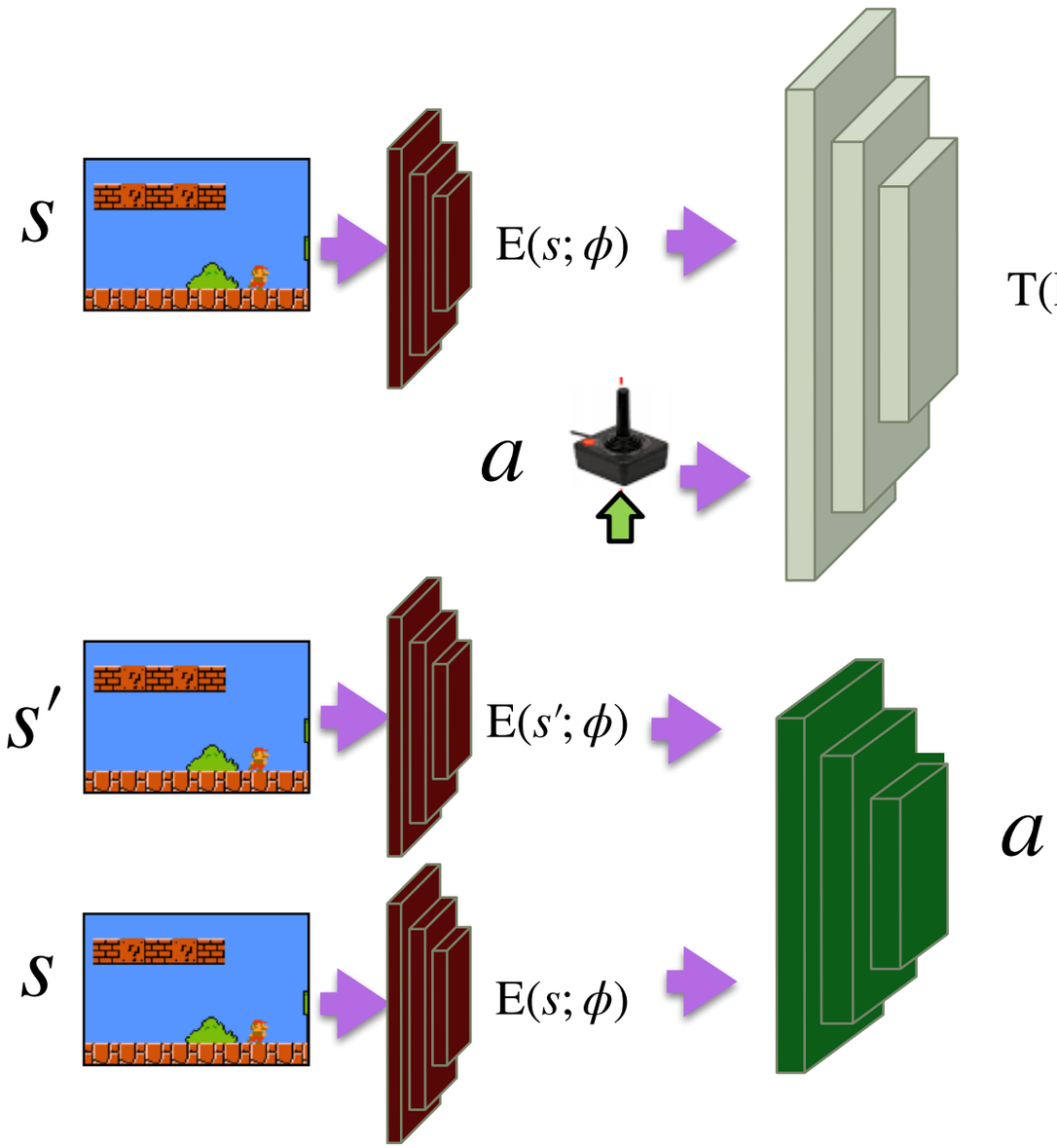


- Let's learn image encoding using autoencoders (to avoid the trivial solution)
- …and suffer the problems of autoencoding reconstruction loss that has little to do with our task

Incentivizing exploration in RL with deep predictive models, Stadie et al.

Learning Visual Dynamics

Exploration reward bonus $\mathcal{B}^t(s, a, s') = \|\mathrm{T}(\mathrm{E}(s;\phi), a;\theta) - \mathrm{E}(s';\phi)\|$



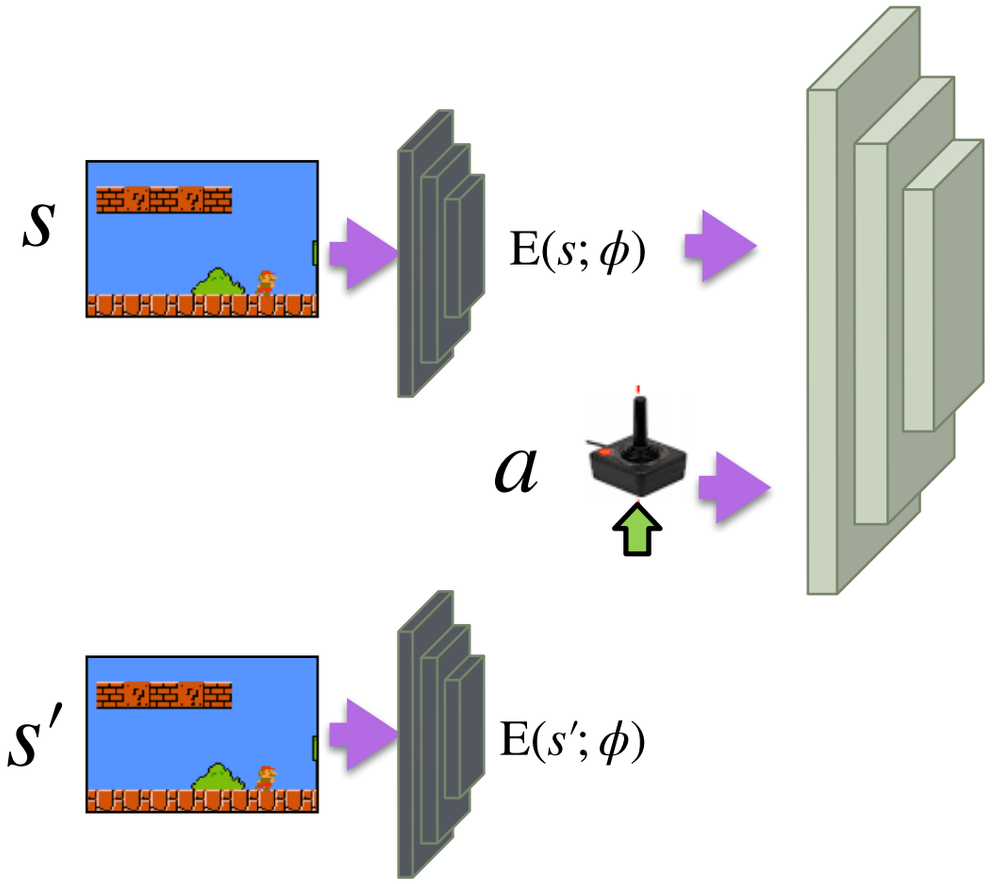
$$\min_{\theta,\phi} \; \|\mathrm{T}(\mathrm{E}(s;\phi), a;\theta) - \mathrm{E}(s';\phi)\| + \|\mathrm{Inv}(\mathrm{E}(s;\phi), \mathrm{E}(s;\phi);\psi) - a\|$$

- Let's couple forward and inverse models (to avoid the trivial solution)
- …then we will only predict things that the agent can control

Curiosity driven exploration with self-supervised prediction, *Pathak*

Learning a Transition function

Exploration reward bonus $\mathcal{B}^t(s, a, s') = \|\mathrm{T}(\mathrm{E}(s;\phi), a;\theta) - \mathrm{E}(s';\phi)\|$



- Let's use random neural networks (networks initialized randomly and frozen thereafter)

Large-scale study of Curiosity-Driven Learning, *Burda et al.*

Task Versus Exploration rewards

Exploration reward bonus $\mathscr{B}^t(s,a,s') = \|\mathrm{T}(\mathrm{E}(s;\phi),a;\theta) - \mathrm{E}(s';\phi)\|$

Only task reward:

$$R(s,a,s') = \underbrace{r(s,a,s')}_{\text{extrinsic}}$$

Task+curiosity:

$$R^t(s,a,s') = \underbrace{r(s,a,s')}_{\text{extrinsic}} + \underbrace{\mathscr{B}^t(s,a,s')}_{\text{intrinsic}}$$

Sparse task + curiosity:

$$R^t(s,a,s') = \underbrace{r^T(s,a,s')}_{\text{extrinsic terminal}} + \underbrace{\mathscr{B}^t(s,a,s')}_{\text{intrinsic}}$$

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Sparse task + curiosity: $R^t(s, a, s') = \underbrace{r^T(s, a, s')}_{\text{extrinsic terminal}} + \underbrace{\mathscr{B}^t(s, a, s')}_{\text{intrinsic}}$

Only curiosity: $R^t(s, a, s') = \underbrace{\mathscr{B}^t(s, a, s')}_{\text{intrinsic}}$

Train an A3C agent under only curiosity reward.
Will it learn to do something useful?

Curiosity driven exploration with self-supervised prediction, Pathak et al.
Large-scale study of Curiosity-Driven Learning, Burda et al.

Policy Transfer

Policies trained with A3C using only curiosity rewards
Prediction error using forward/inverse model coupling

Trained on Level-1

Testing on Level-2

Large-scale study of Curiosity-Driven Learning, *Burda et al.*

Limitation of Prediction Error as Bonus

- Agent will be rewarded even though the model cannot improve.
- The agent is attracted forever in the most noisy states, with unpredictable outcomes.
- If we give the agent a TV and a remote, it becomes a couch potato!

Large-scale study of Curiosity-Driven Learning, Burda et al.

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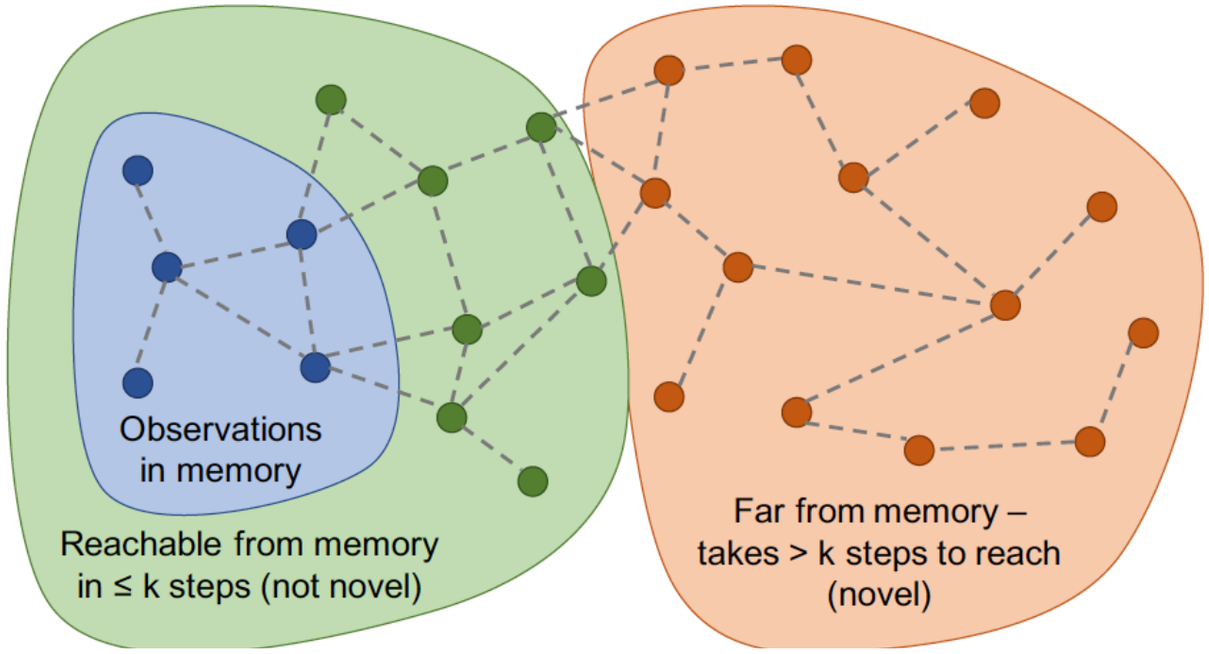
EPISODIC CURIOSITY THROUGH REACHABILITY

Nikolay Savinov [*1] **Anton Raichuk** [*1] **Raphaël Marinier** [*1] **Damien Vincent** [*1]
Marc Pollefeys [3] **Timothy Lillicrap** [2] **Sylvain Gelly** [1]

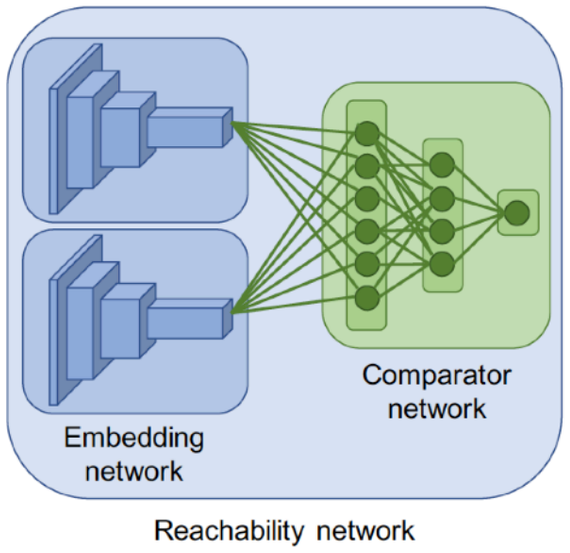
[1]Google Brain, [2]DeepMind, [3]ETH Zürich

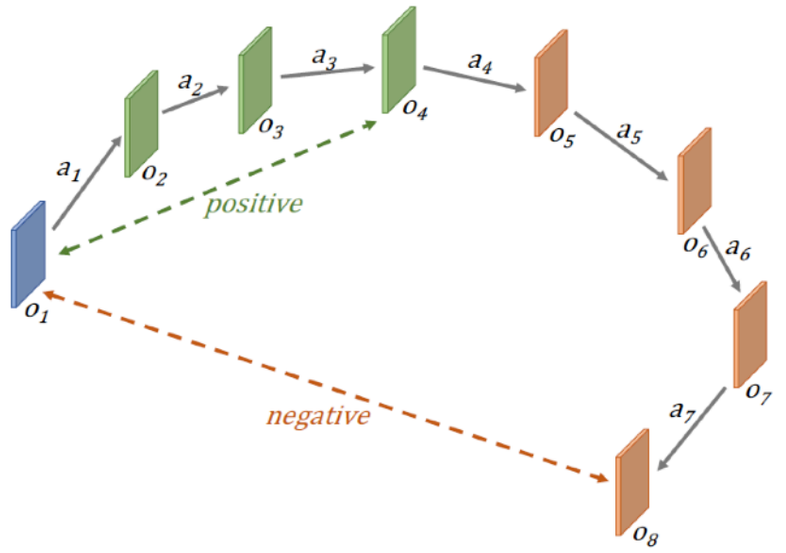
- We will be using augmented rewards as before
  $R^t(s, a, s') = \underbrace{r(s, a, s')}_{extrinsic} + \underbrace{\mathscr{B}^t(s, \mathscr{M})}_{intrinsic}$, where $\mathscr{M}$ is a non-parametric memory structure populated with embeddings of past image observations.
- Curiosity reward will use a comparator neural net, that takes as input two images and predicts whether they are close (few actions apart) or far
- We will plug those rewards into PPO, a model-free RL method

non-parametric memory structure



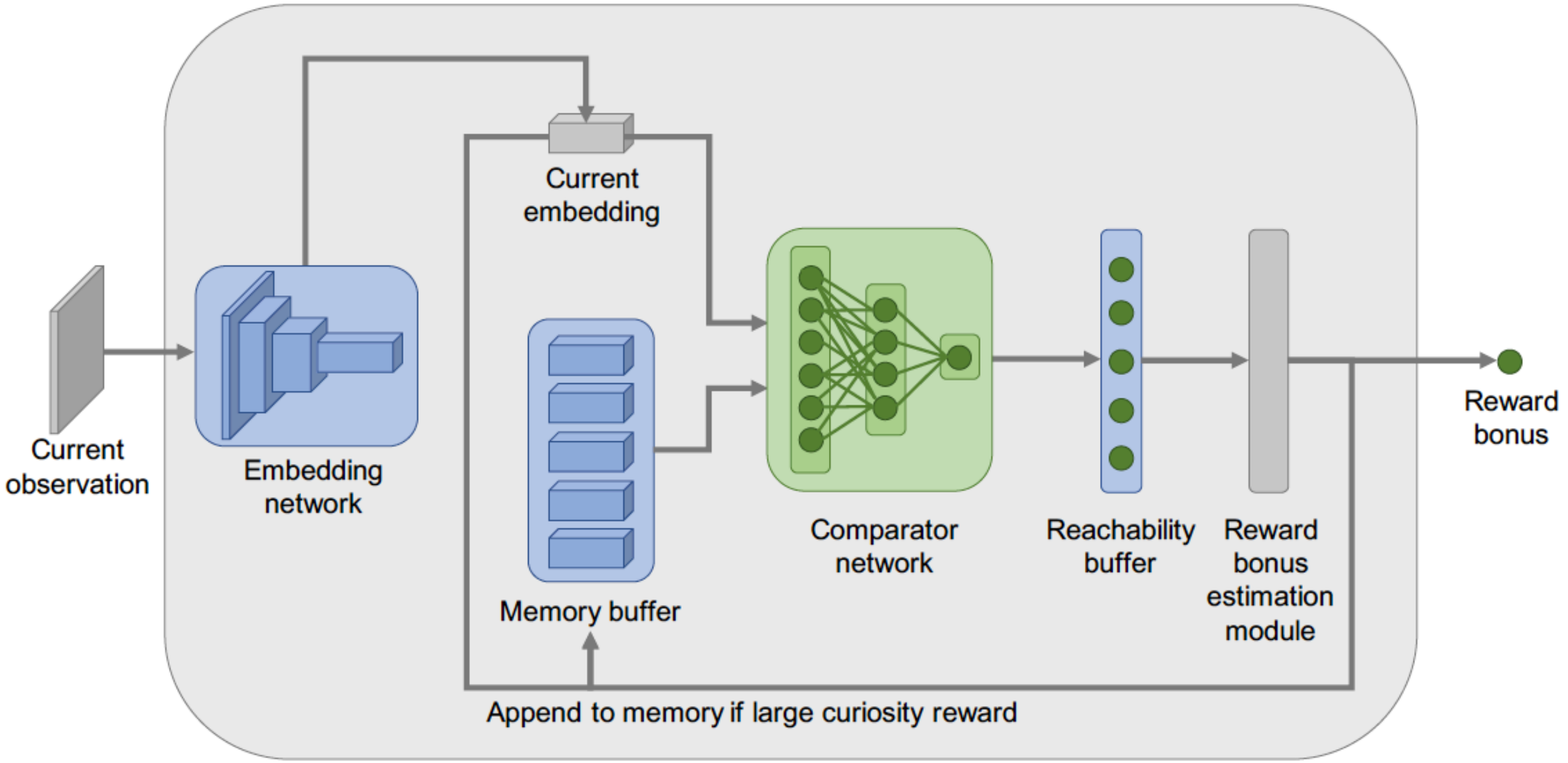
comparator network trained with temporal contrastive learning





$$\mathscr{L}_{\phi}(o, o^{+}, o^{-}) = \|E(o, \phi) - E(o^{+}, \phi)\| + \max(0, \gamma - \|E(o, \phi) - E(o^{-}, \phi)\|)$$

At each time step the agent compares the current observation with the ones in memory. If it is novel (takes more steps to reach than a threshold) then agent get rewarded, and the novel observation is added into memory.


Current
embedding
Current
observation
Embedding
network
Memory buffer
Comparator
network
Reachability
buffer
Reward
bonus
estimation
module
Reward
bonus
Append to memory if large curiosity reward

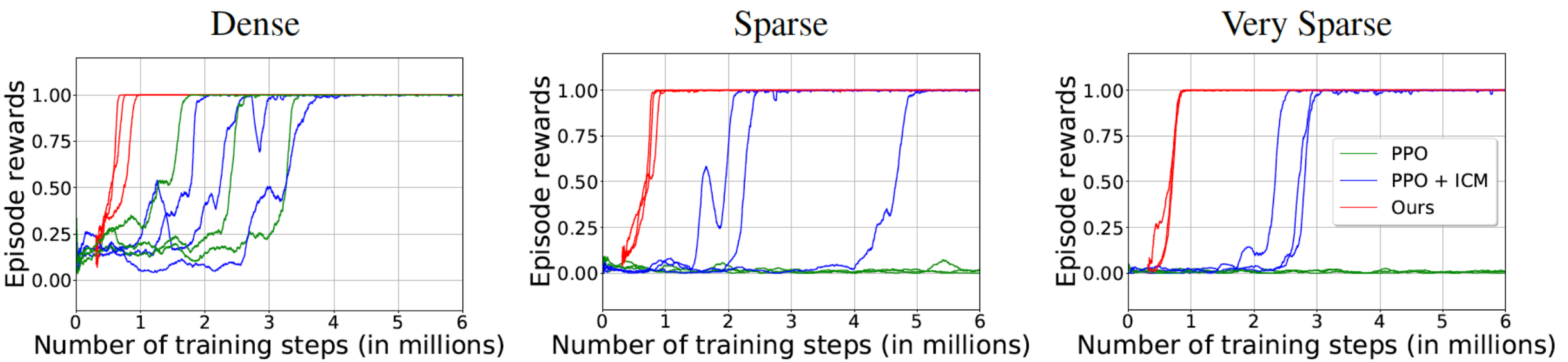


Figure 6: Task reward as a function of training step for *VizDoom* tasks. Higher is better. We use the offline version of our algorithm and shift the curves for our method by the number of environment steps used to train R-network — so the comparison is fair. We run every method with a repeat of 3 (same as in prior work (Pathak et al., 2017)) and show all runs. No seed tuning is performed.

Go-Explore: a New Approach for Hard-Exploration Problems

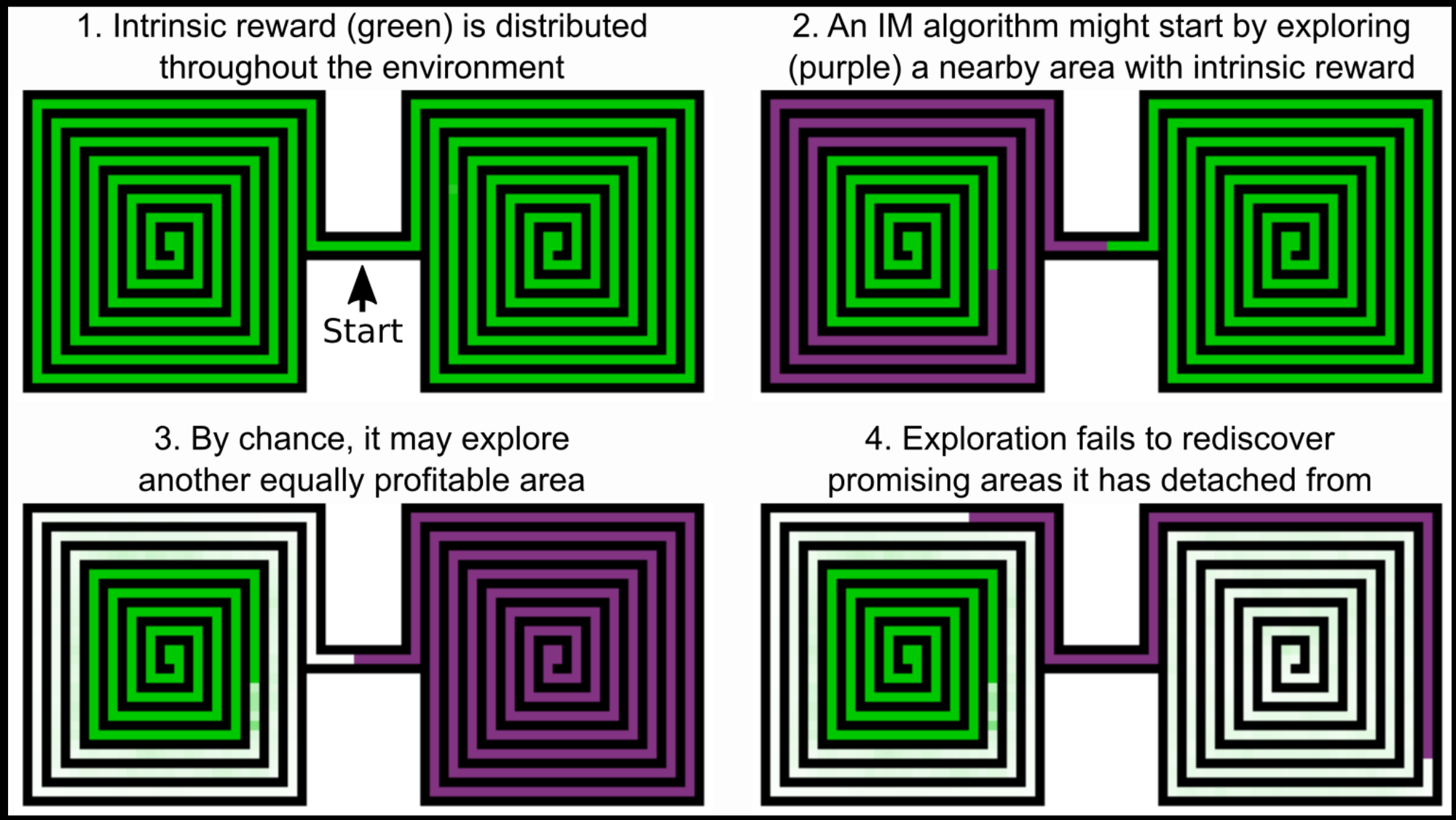
Adrien Ecoffet **Joost Huizinga** **Joel Lehman** **Kenneth O. Stanley*** **Jeff Clune***
Uber AI Labs
San Francisco, CA 94103
adrienle,jhuizinga,joel.lehman,kstanley,jeffclune@uber.com
*Co-senior authors

Structured memory as state connectivity map

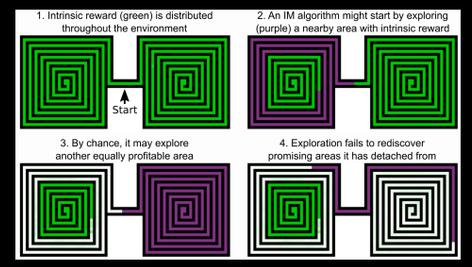
Intrinsic Motivation

- Helps, but why doesn’t it work better?

“Detachment”


1. Intrinsic reward (green) is distributed throughout the environment
Start
2. An IM algorithm might start by exploring (purple) a nearby area with intrinsic reward
3. By chance, it may explore another equally profitable area
4. Exploration fails to rediscover promising areas it has detached from

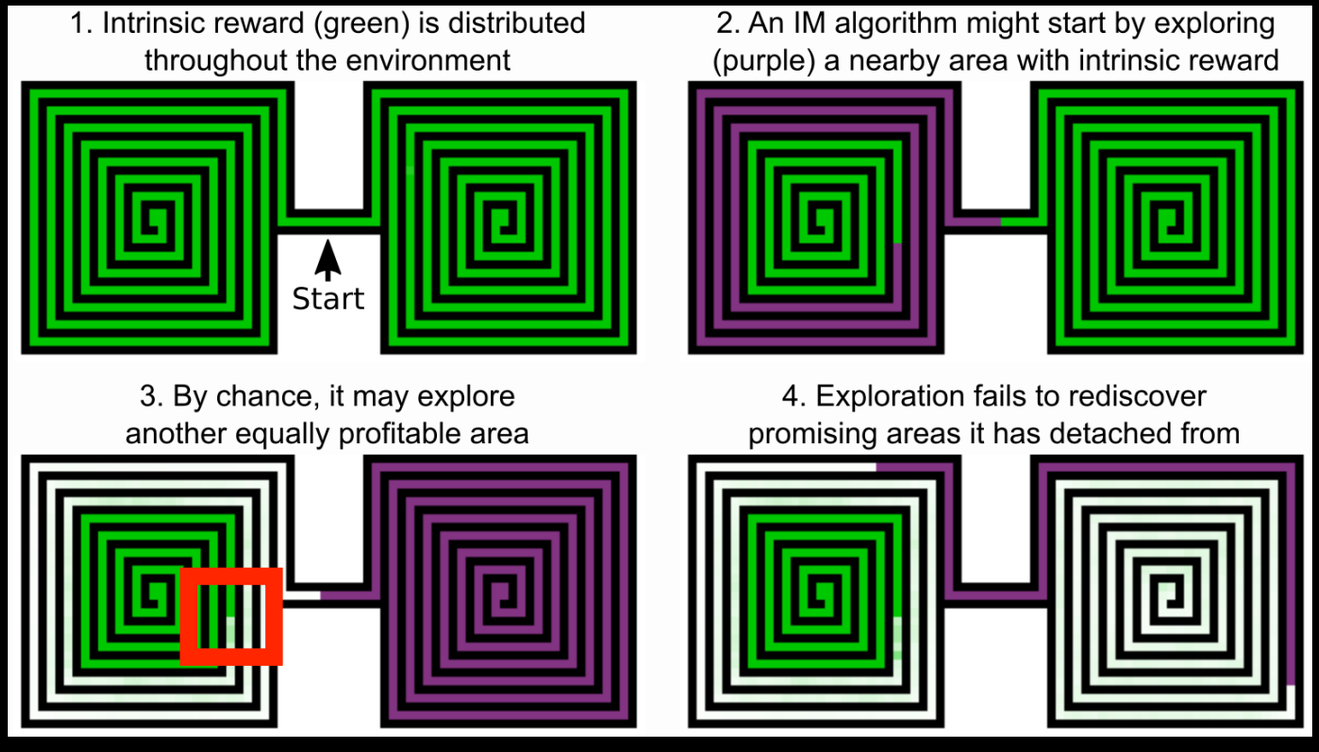
Detachment



- Replay buffers
  - Should remember in theory, but forget/fail in practice
    - replay buffer size must be very large
    - but that causes optimization/stability issues

Detachment

- Proposal: explicitly remember
  - where promising locations are
  - how to get back to them



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Book-keep an archive of trajectories that—accidentally through exploration—reached a particular state in the world and the state reached.

We will be updating the archive with:

- New states reached and the corresponding trajectories
- Better (shorter) trajectories to reach already archived states
- We will be resetting ourselves to such states and continue exploring updating our state connectivity map.

Then, we will turn such single trajectories into robust policies.

“Derailment”

- Most RL algorithms:
  - take promising policy, perturb it, hope it explores further
  - most likely breaks policy!
    - especially as length, complexity, & precision of sequence increases

Derailment

- Insight: First return, then explore

Derailment

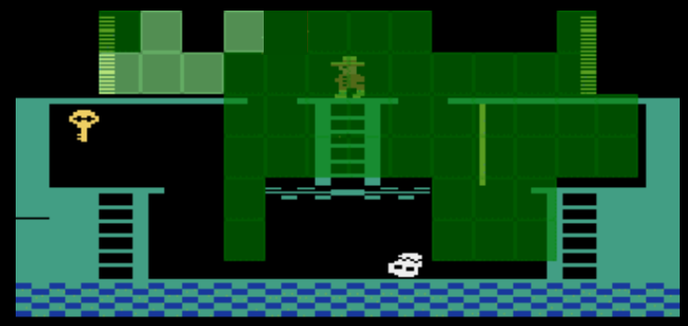
- Insight: First return, then explore
  - counter: hurt robustness?

Go-Explore Strategy

- Phase 1: First solve
- Phase 2: Then robustify
  - pay the cost to robustify only once you know *what* needs to be robustified

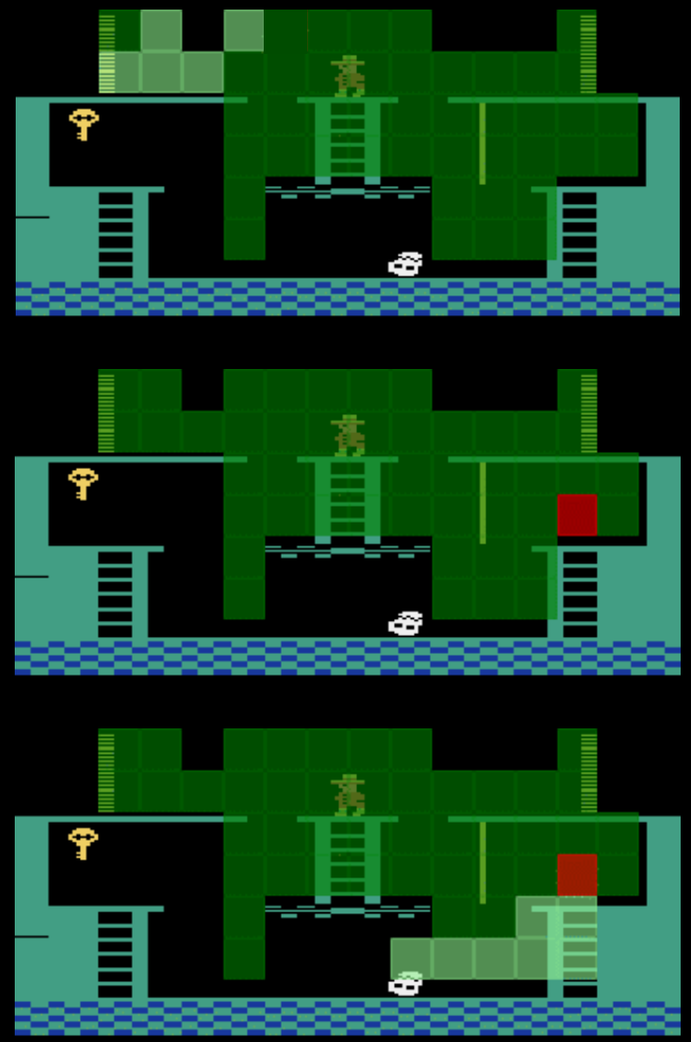
Go-Explore: Phase 1

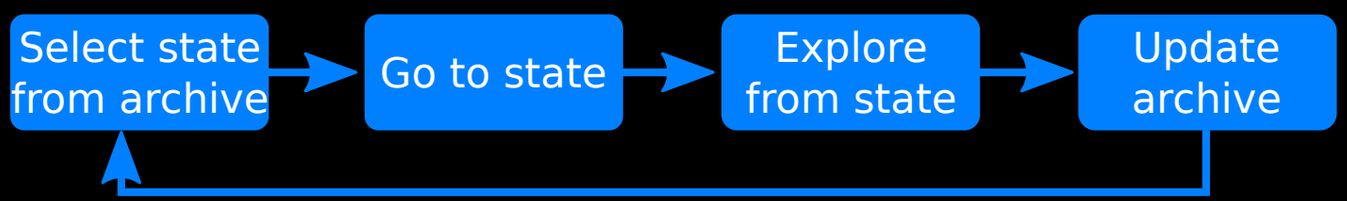
- initialization:
  - take random actions, store cells visited



Go-Explore: Phase 1

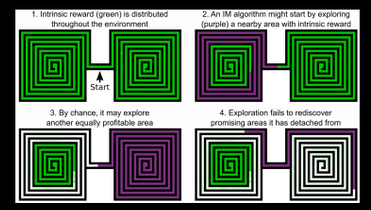
- Phase 1: explore until solved
  A. choose a cell from archive
  B. Go back to it
  C. Explore from it
  D. add newly found cells to archive
    - if better, replace old way of reaching cell



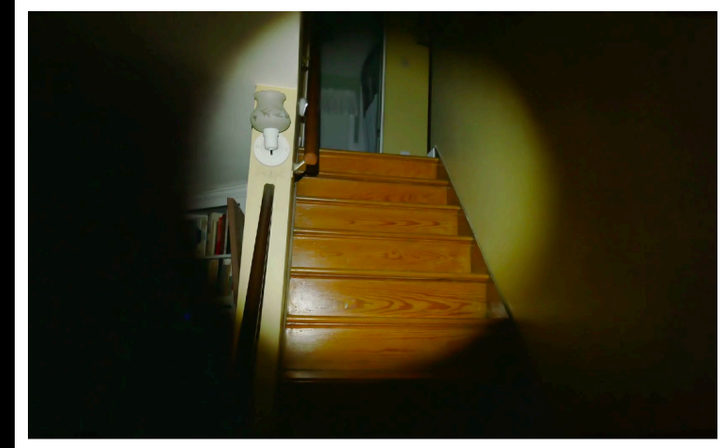


Avoids Detachment

By Remembering Promising Exploration Stepping Stones



- Intrinsic motivation:
  - narrow beam mining intrinsic motivation and moving on

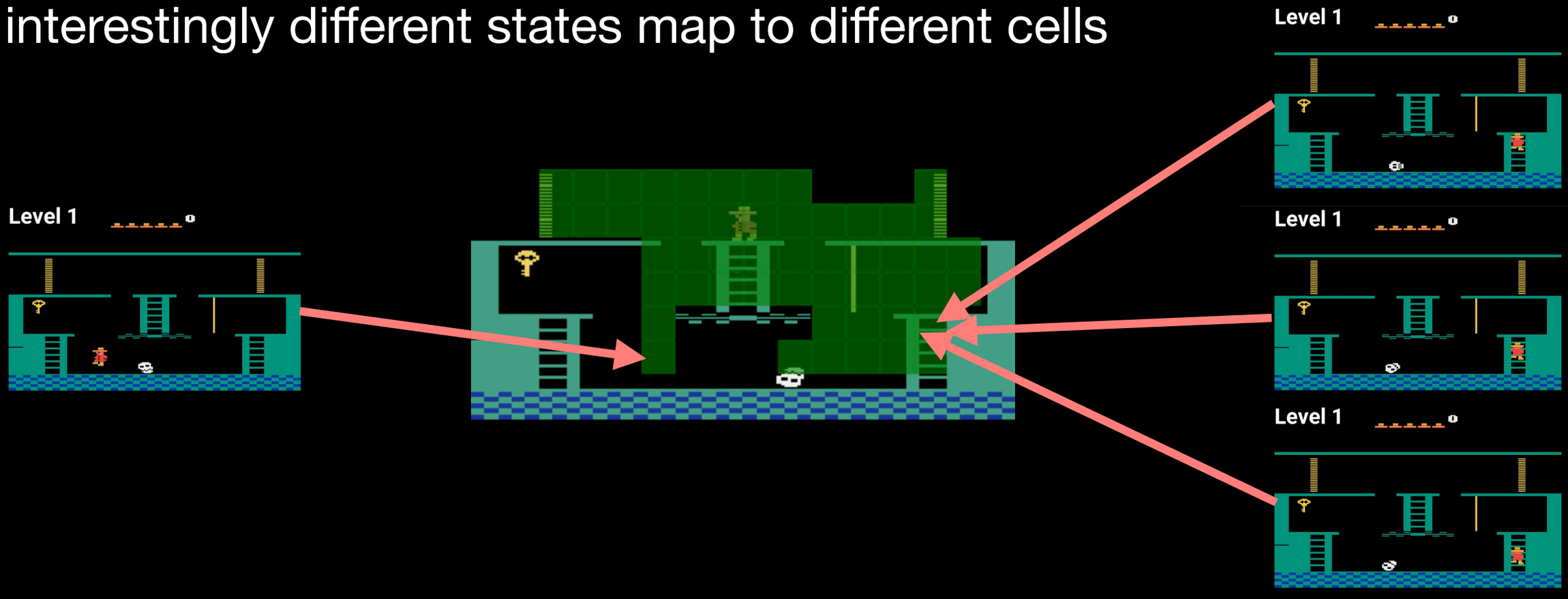


- Go-Explore
  - continuously expands sphere of knowledge

We are building a room connectivity map of the house!

Cell Representations

- For large state spaces (e.g. Atari), need conflation
  - similar states map to same cell
  - interestingly different states map to different cells

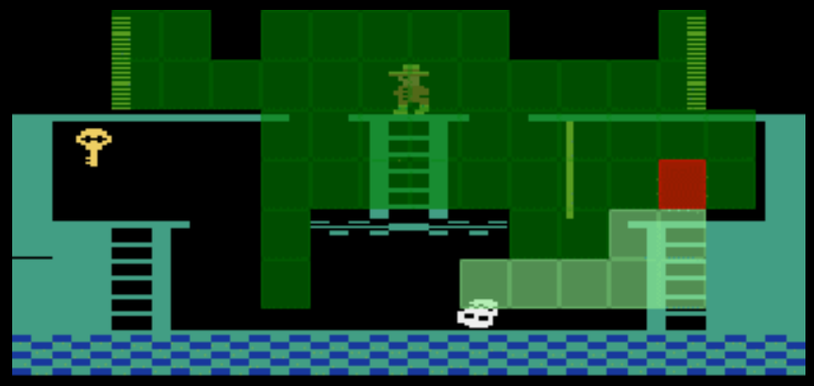


Cell Representations

- First attempt: downsampling images
  - dumb
  - fast
  - no game-specific domain knowledge

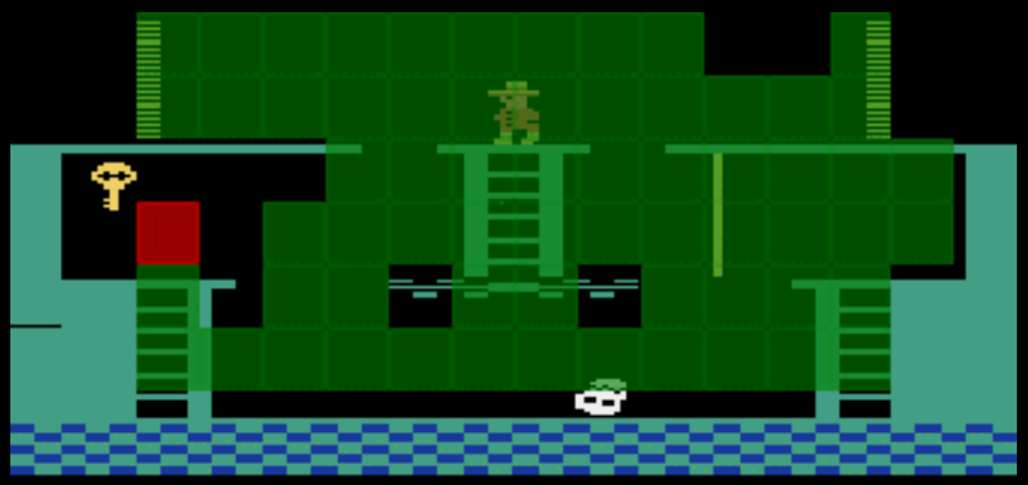
Choosing Cells

- Prefer cells that are
  - led to new states (productive)
  - less tested (newer)



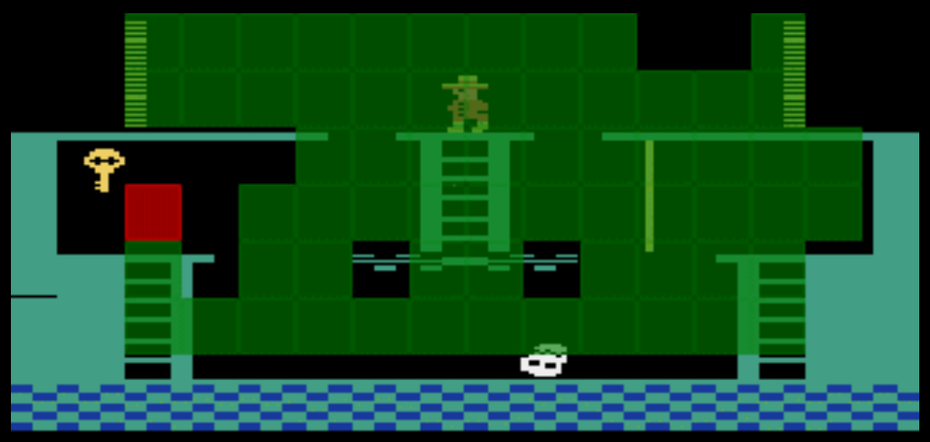
Returning to Cells

- resettable & deterministic: reset state (or replay actions)
- stochastic environment:
  - goal-conditioned policy
    - e.g. UVFA (Schaul et al. 2015), HER (Andrychowicz et al. 2017)
  - other ideas



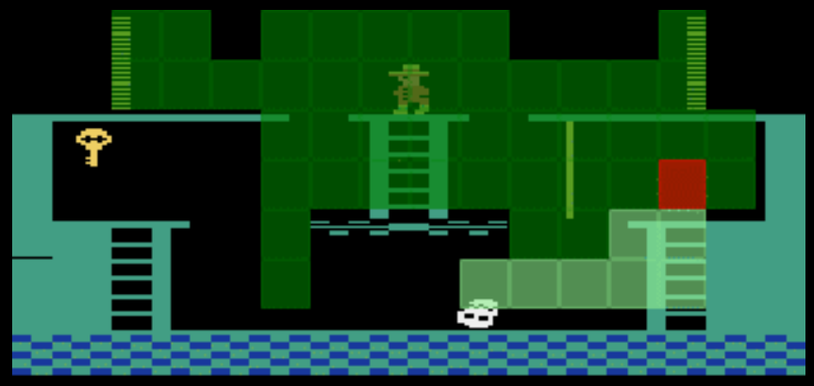
Returning to Cells

- save action-sequence trajectories to cells
  - open loop
  - no neural network!

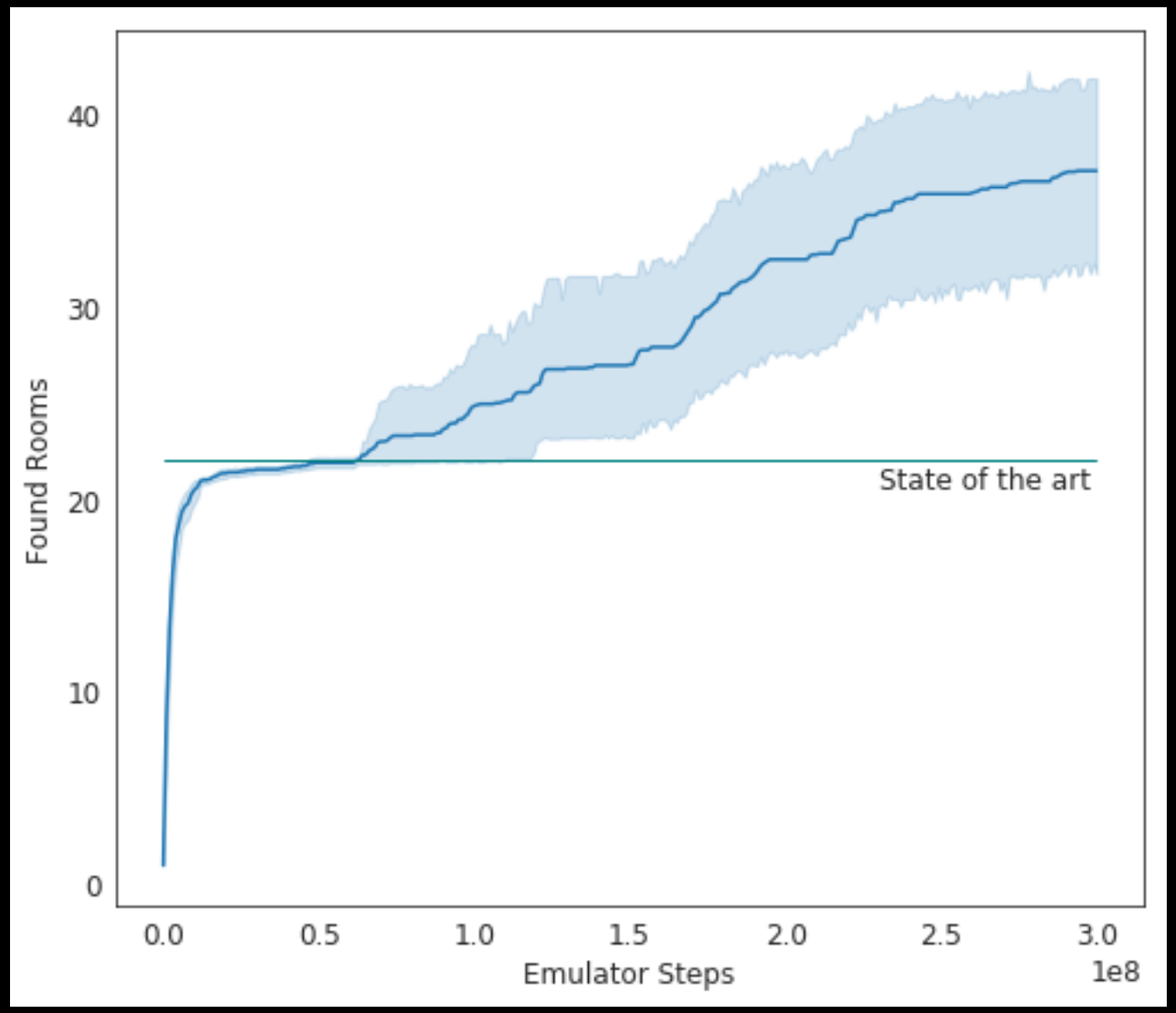


Exploration

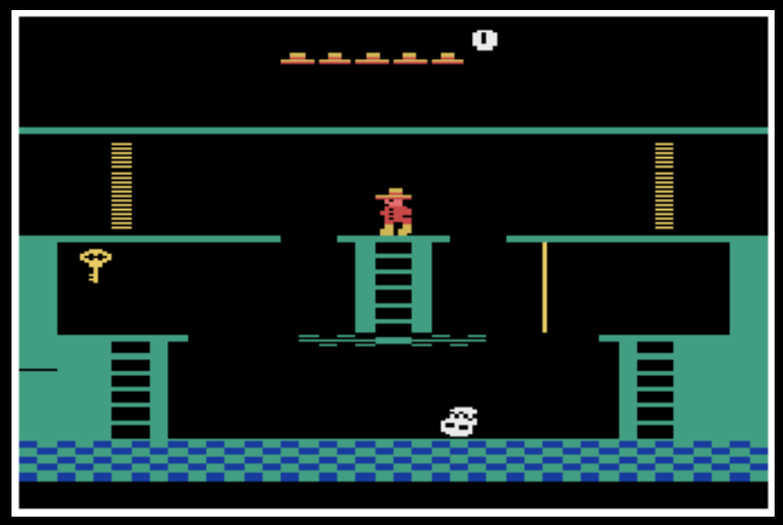
- after returning to a cell
- take random actions (k=100)



Montezuma's Revenge Results: Phase 1



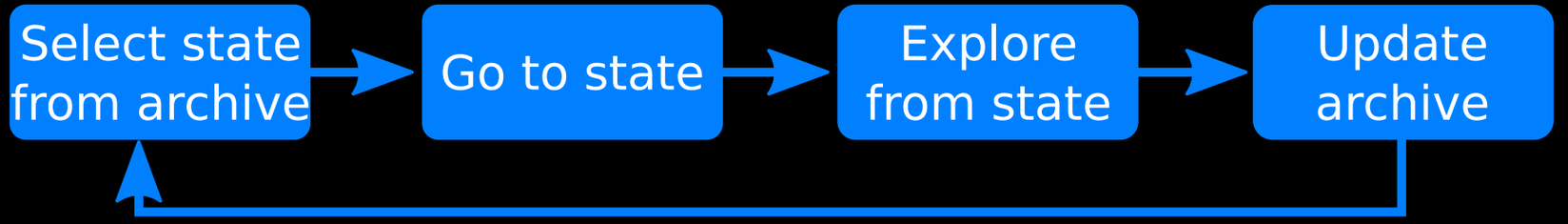
- Solves level 1 65% of runs



Go-Explore

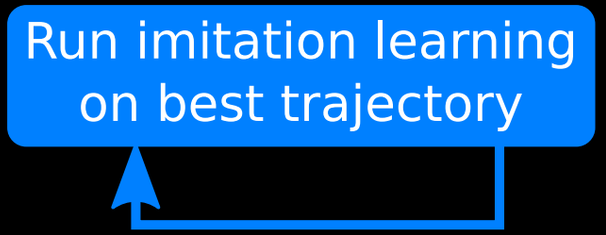
Separates learning a solution into two phases

Phase 1: Explore Until Solved

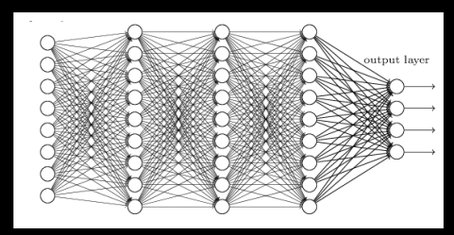


no neural networks
(in current work)

Phase 2: Robustify
(if necessary)



produces neural network
robust to stochasticity



Phase 2: Robustify

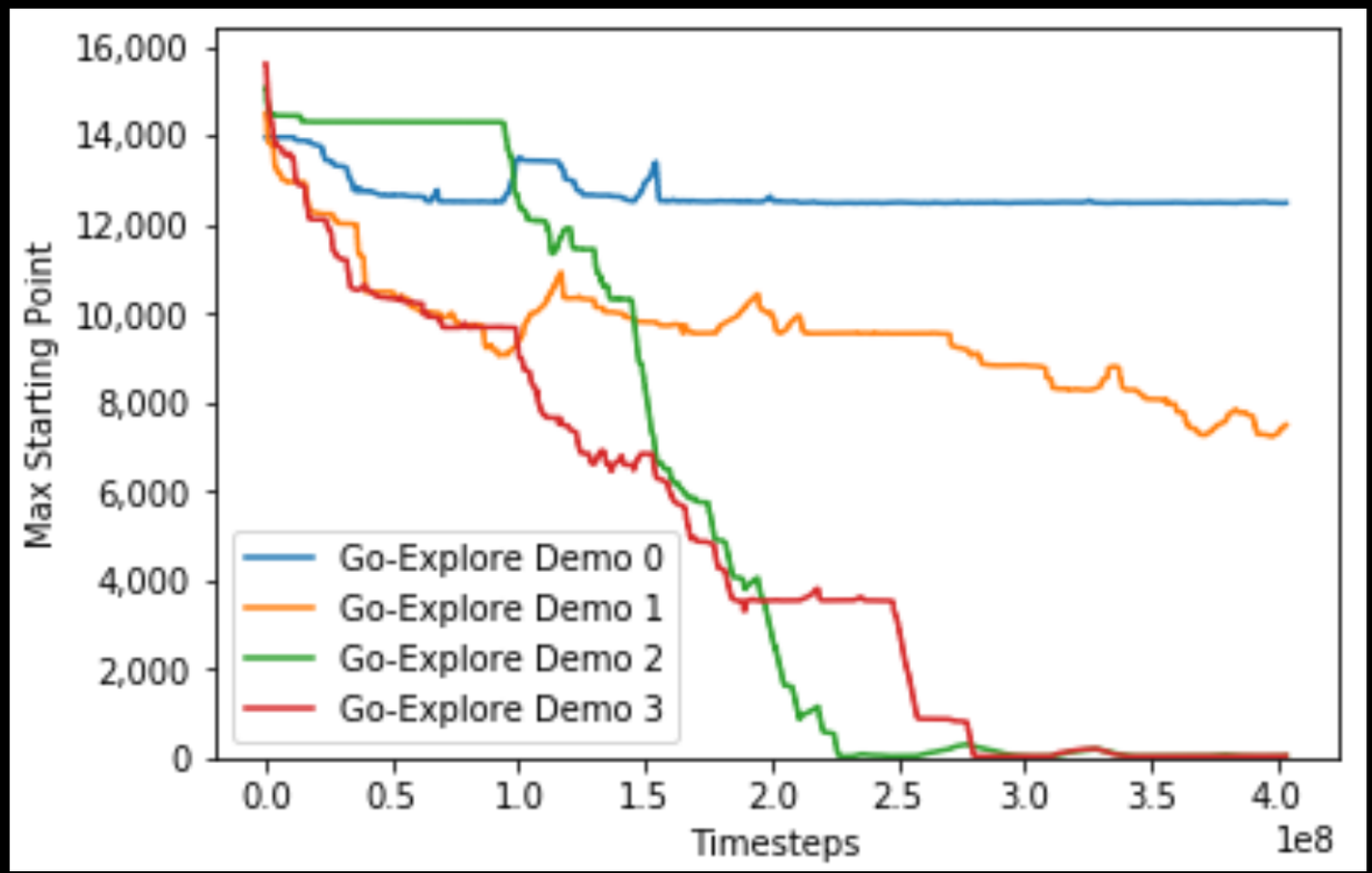
- Imitation learning can work well with human demonstrations
  - including on Montezuma's Revenge & Pitfall (e.g. Aytar 2018)
- Go-Explore Phase 1 generates solution demonstrations
  - automatically
  - quickly
  - cheaply
  - as many as you want

Phase 2: Robustify

- Most imitation learning algorithms should work
- We chose the “backward algorithm”
  - from Salimans & Chen 2018 (this workshop!)
  - similar: Backplay from Resnick et al. 2018

Many Demonstrations

- Backwards Imitation somewhat unreliable from one demonstration
- We modified it to learn from many
  - here, 4
- Add no-ops at beginning
- Success rate: 100%



Example Successful Attempt

From few trajectories to robust policies!

Learning Montezuma's Revenge from a Single Demonstration

Tim Salimans
OpenAI, Google Brain

Richard Chen
OpenAI, Happy Elements Inc.

- What makes model-free RL hard is distant in time and sparse rewards
- Insights:
  - Do not imitate the trajectory actions! Just reset from a state along the trajectory instead from the initial state.
  - Reset progressively earlier in time. Make the task easier to solve by decomposing it into a curriculum of subtasks requiring short action sequences.

The hopelessness of learning from distant rewards

Imagine we need 5 steps till the first reward (getting a key).

$$p(\text{get first key}) = p(\text{get down ladder 1}) * p(\text{get down rope}) * \\ p(\text{get down ladder 2}) * p(\text{jump over skull}) * p(\text{get up ladder 3}).$$

Taking uniformly random actions (naive exploration) in Montezuma's Revenge only produces a reward about once in every half a million steps. This probability decreases

- as the number of actions increases and
- the time-horizon till reward increases.

reset to a state from the demo

Algorithm 1 Demonstration-Initialized Rollout Worker

Input: a human demonstration $\{(\tilde{s}_t, \tilde{a}_t, \tilde{r}_t, \tilde{s}_{t+1}, \tilde{d}_t)\}_{t=0}^{T}$, number of starting points D, effective RNN memory length K, batch rollout length L.
Initialize starting point τ^* by sampling uniformly from $\{\tau - D, \ldots, \tau\}$
Initialize environment to demonstration state $\tilde{s}_{\tau^*}$
Initialize time counter $i = \tau^* - K$
while TRUE **do**
  Get latest policy $\pi(\theta)$ from optimizer
  Get latest reset point τ from optimizer
  Initialize success counter $W = 0$
  Initialize batch $\mathcal{D} = \{\}$
  for step in $0, \ldots, L-1$ **do**
    if $i \geq \tau^*$ **then**
      Sample action $a_i \sim \pi(s_i, \theta)$
      Take action a_i in the environment
      Receive reward r_i, next state s_{i+1} and done signal d_{i+1}
      $m_i = \text{TRUE}$ ▷ We can train on this data
    else ▷ Replay demonstration to initialize RNN state of policy
      Copy data from demonstration $a_i = \tilde{a}_i, r_i = \tilde{r}_i, s_{i+1} = \tilde{s}_{i+1}, d_i = d_i$.
      $m_i = \text{FALSE}$ ▷ We should mask out this transition in training
    end if
    Add data $\{s_i, a_i, r_i, s_{i+1}, d_i, m_i\}$ to batch $\mathcal{D}$
    Increment time counter $i \leftarrow i + 1$
    if $d_i = \text{TRUE}$ **then**
      if $\sum_{t \geq \tau^*} r_t \geq \sum_{t \geq \tau^*} \tilde{r}_t$ **then** ▷ As good as demo
        $W \leftarrow W + 1$
      end if
      Sample next starting starting point τ^* uniformly from $\{\tau - D, ..., \tau\}$
      Set time counter $i \leftarrow \tau^* - K$
      Reset environment to state $\tilde{s}_{\tau^*}$
    end if
  end for
  Send batch $\mathcal{D}$ and counter W to optimizer
end while

Algorithm 2 Optimizer

Input: number of parallel agents M, starting point shift size Δ, success threshold ρ, initial parameters θ_0, demonstration length T, learning algorithm $\mathcal{A}$ (e.g. PPO, A3C, Impala, etc.)
Set the reset point $\tau = T$ to the end of the demonstration
Start rollout workers $i = 0, \ldots, M-1$
while $\tau > 0$ **do**
  Gather data $\mathcal{D} = \{\mathcal{D}_0, \ldots, \mathcal{D}_{M-1}\}$ from rollout workers
  if $\sum_{\mathcal{D}}[W_i] / \sum_{\mathcal{D}}[d_{i,t}] \geq \rho$ **then** ▷ The workers are successful sufficiently often
    $\tau \leftarrow \tau - \Delta$
  end if
  $\theta \leftarrow \mathcal{A}(\theta, \mathcal{D})$ ▷ Make sure to mask out demo transitions
  Broadcast θ, τ to rollout workers
end while

Reset time point to earlier in time

Solve the subtask from τ till T with standard model-free RL

I do not start from scratch!
I start from the policy learnt from the previous time segment

Learning Montezuma's Revenge from a Single Demonstration, Salimans and Chen

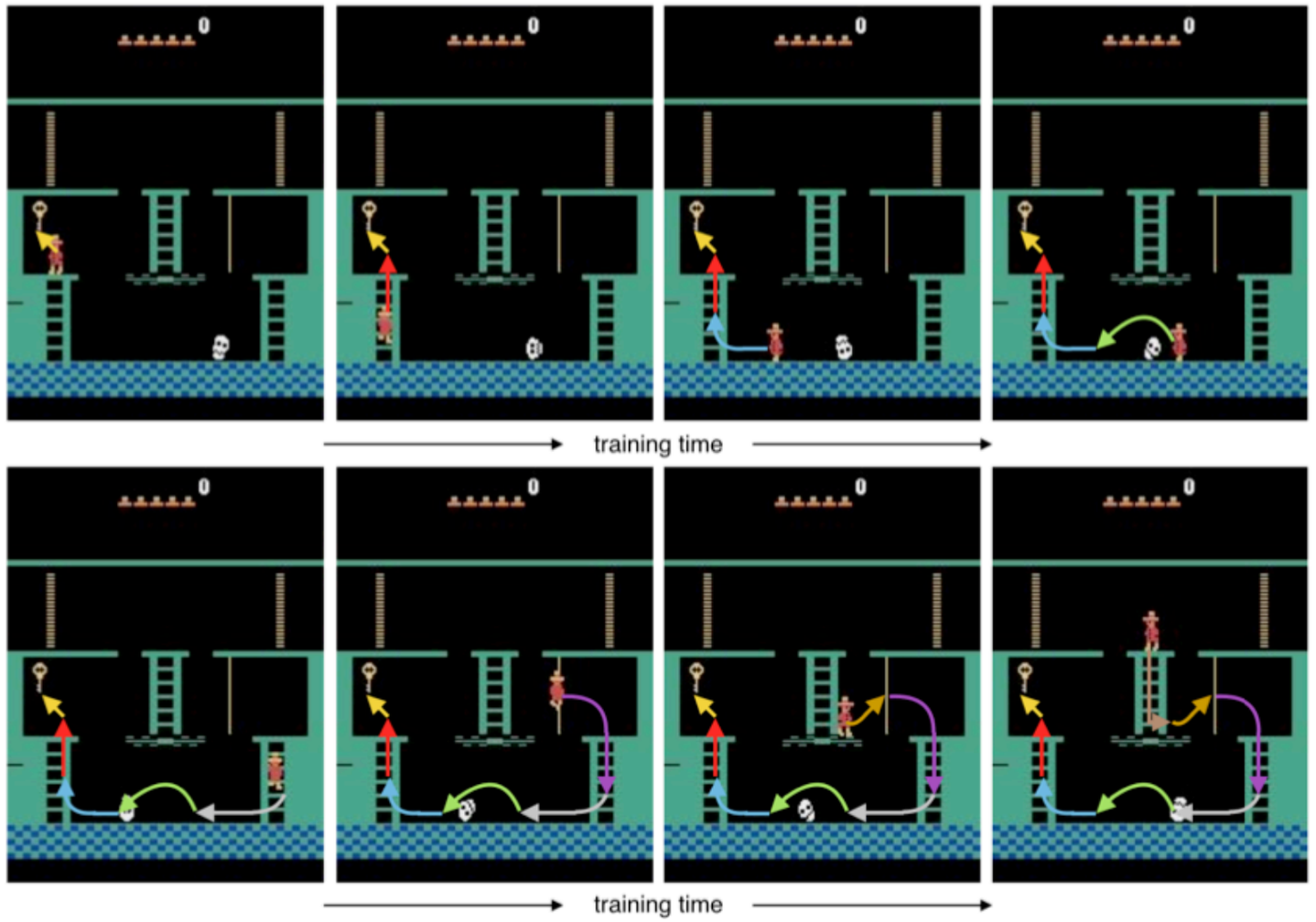


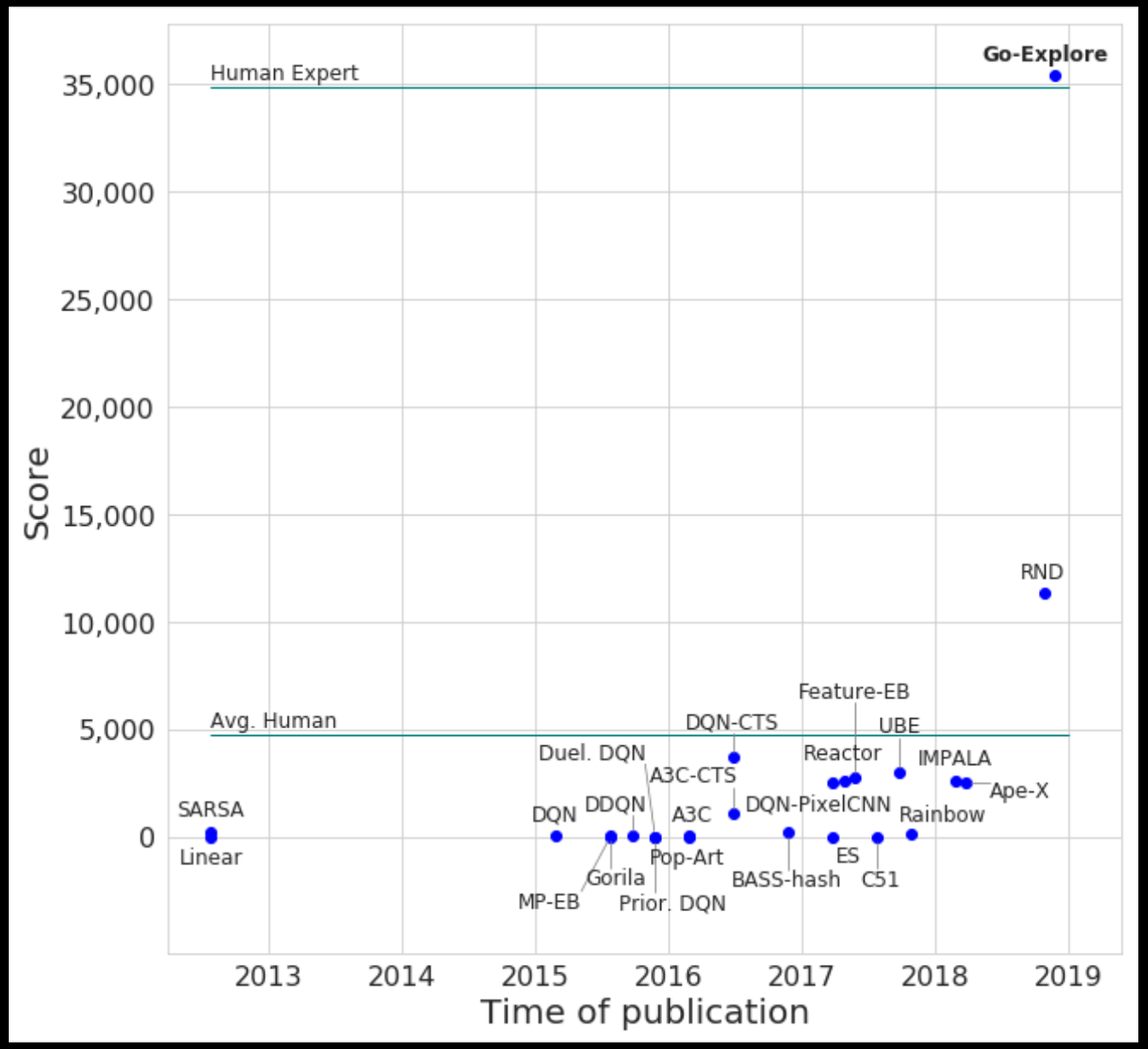
Figure 1: Impression of our agent learning to reach the first key in Montezuma's Revenge using RL and starting each episode from a demonstration state. When our agent starts playing the game, we place it right in front of the key, requiring it to only take a single jump to find success. After our agent has learned to do this consistently, we slowly move the starting point back in time. Our agent might then find itself halfway up the ladder that leads to the key. Once it learns to climb the ladder from there, we can have it start at the point where it needs to jump over the skull. After it learns to do that, we can have it start on the rope leading to the floor of the room, etc. Eventually, the agent starts in the original starting state of the game and is able to reach the key completely by itself.

Approach	Score
Count-based exploration (Ostrovski et al. [2017])	3,705.5
Unifying count-based exploration (Bellemare et al. [2016])	6,600
DQfD (Hester et al. [2017])	4,739.6
Ape-X DQfD (Pohlen et al. [2018])	29,384
Playing by watching Youtube (Aytar et al. [2018])	41,098
Ours	74,500

Table 1: Score comparison on Montezuma's Revenge

Results with Robust Deep Neural Networks

- 3x previous state of the art!
- Robust to stochasticity
  - random # no-ops up to 30
- No game-specific domain knowledge

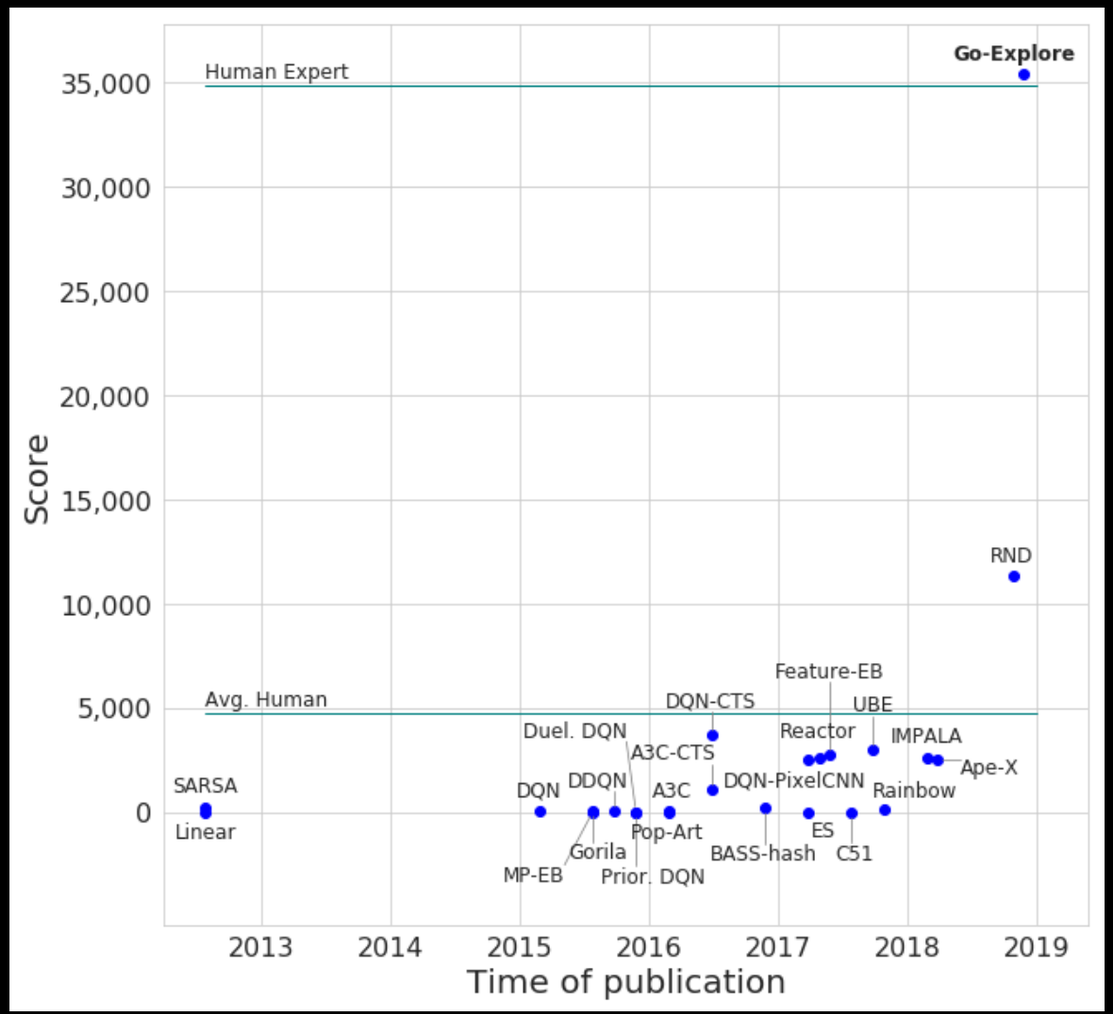


Go-Explore created a healthy debate

- When should we require stochasticity?
  - test time (only)?
  - training time too?

Stochasticity at Test Time

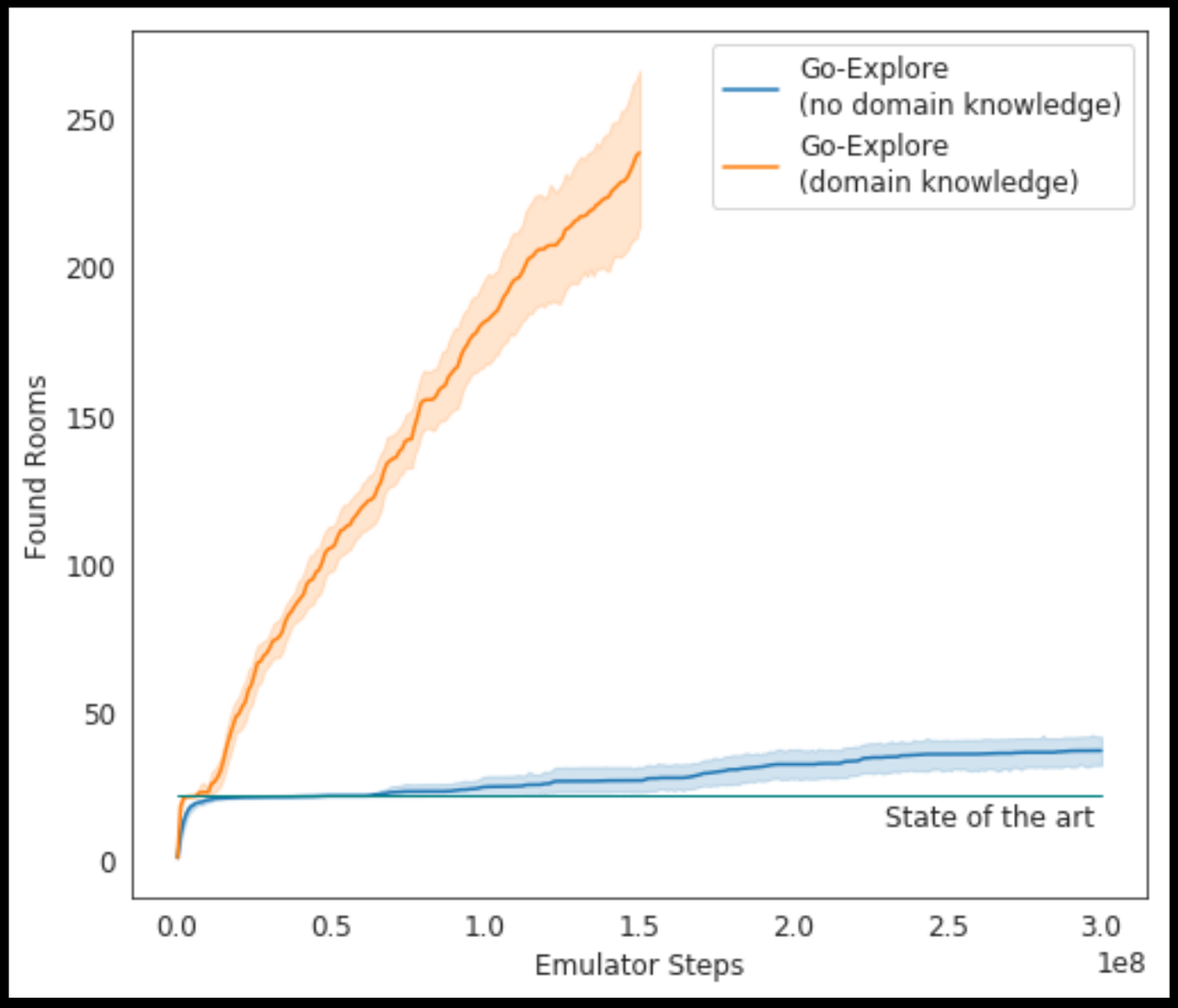
- Classic way: random number up to 30 no-ops



Adding Domain Knowledge

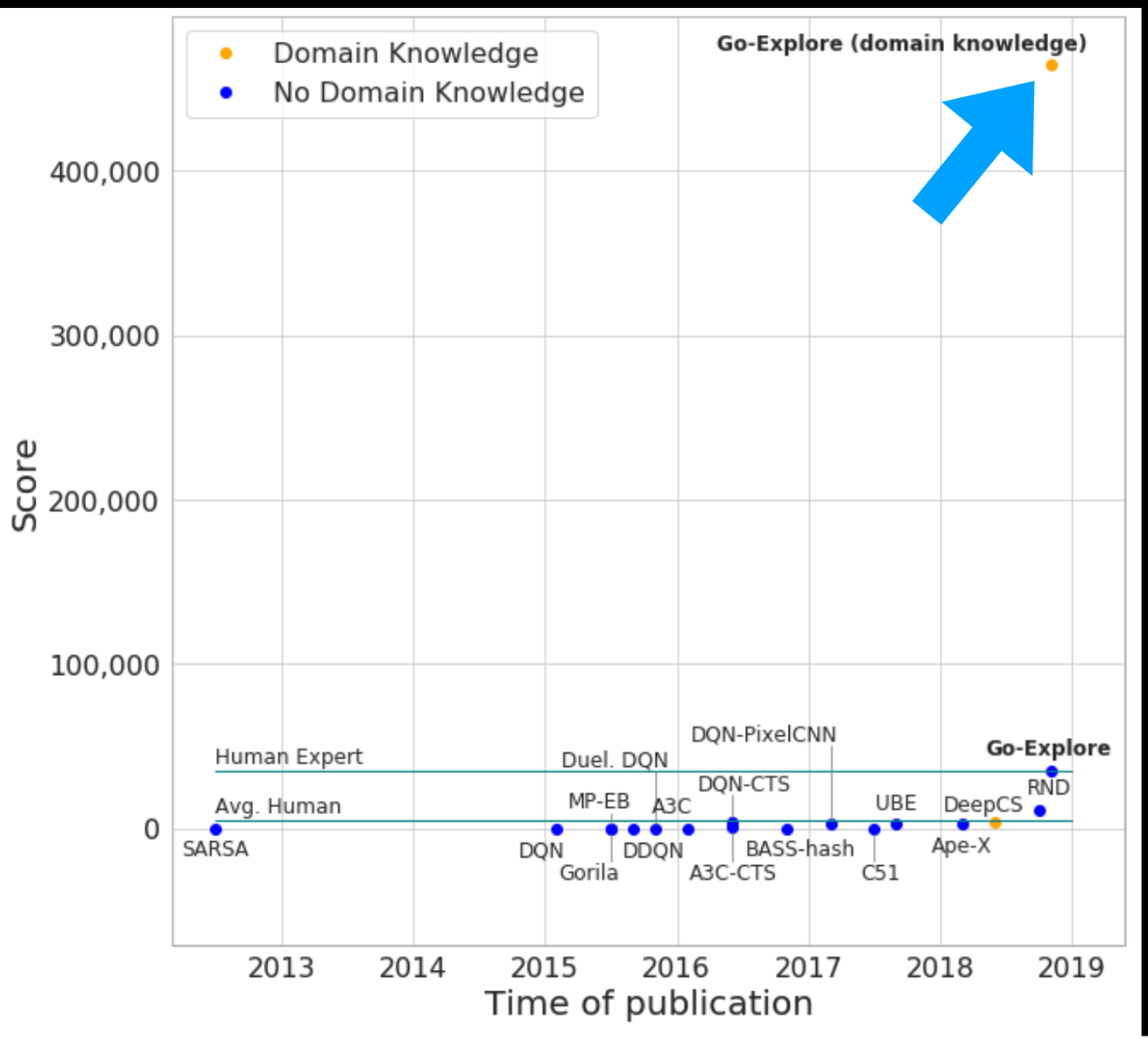
- Go-Explore can add it via cell representation
  - Important notes:
    - final post-robustification policies still play from pixels only
      - do not consume domain knowledge at eval time
      - wrote simple code to extract info from pixels (not emulator)
  - Montezuma's Revenge
    - unique combinations of: x, y location, room, level, numKeysHeld
  - Pitfall
    - <x, y> location, room

Montezuma's Results with Domain Knowledge
Phase 1: Exploration (deterministic eval)



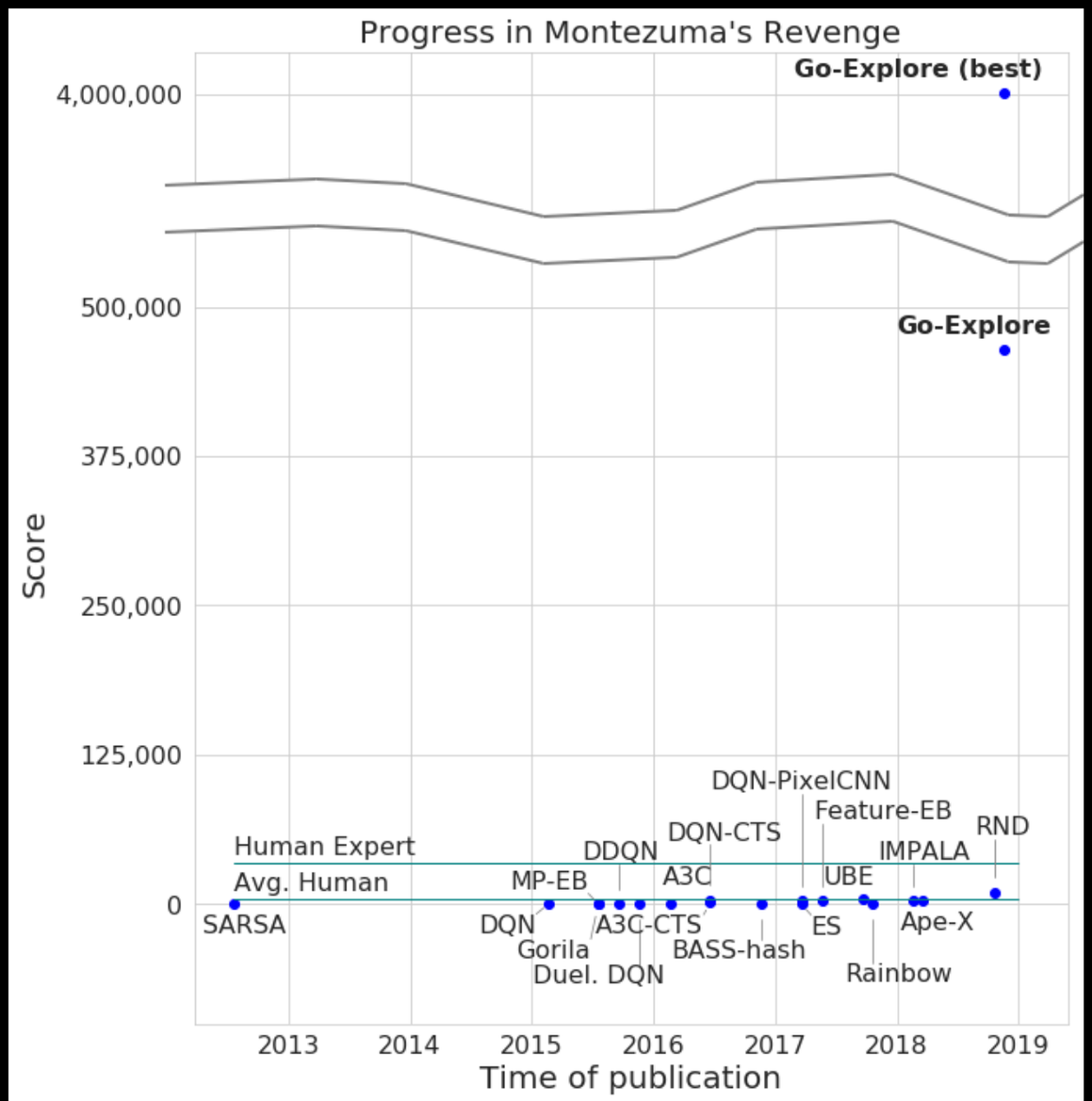
- Solves 9 levels on average
- in half the time

Results with Robust Deep Neural Networks



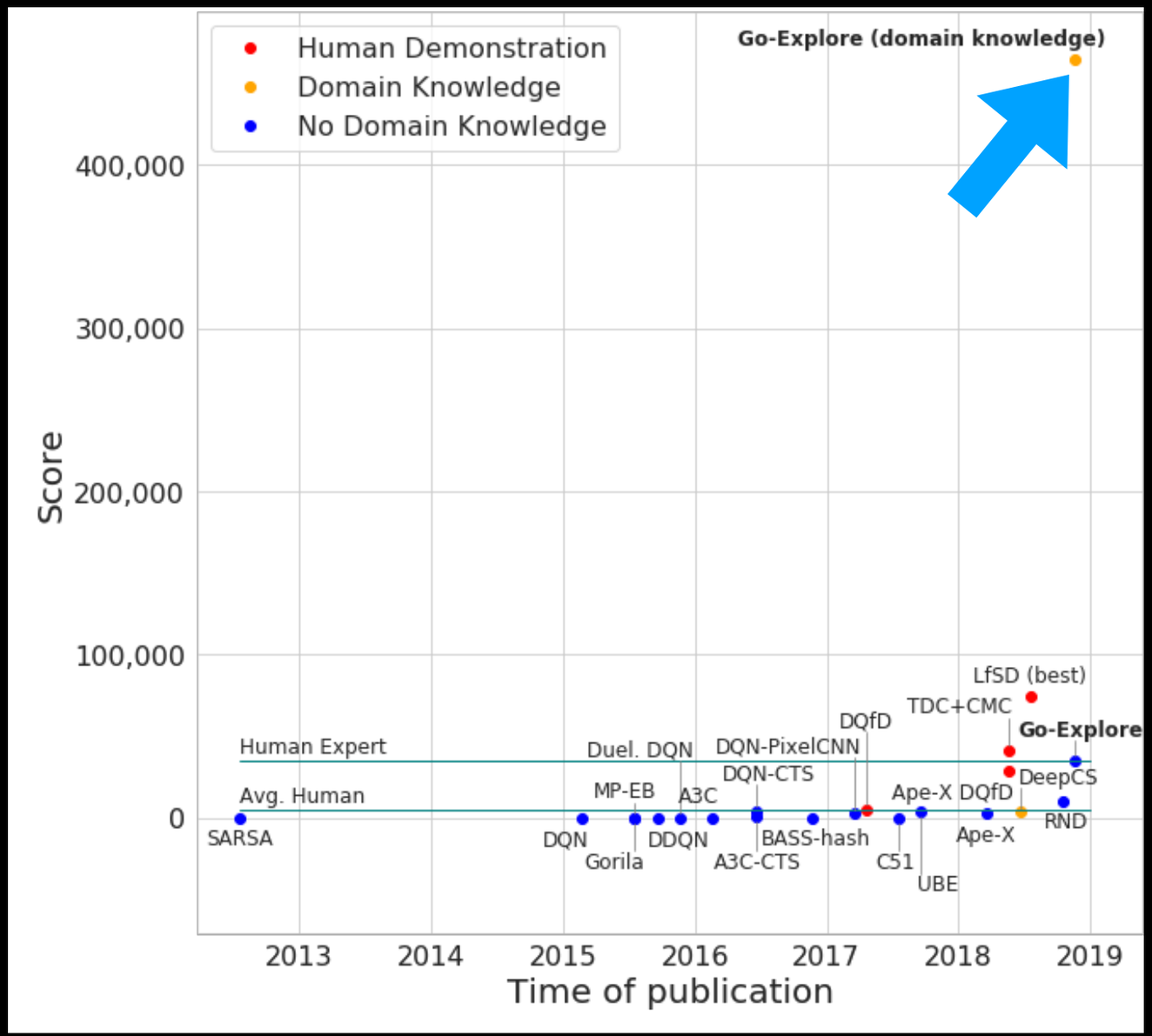
- Solves all 3 unique levels
- Levels 3+ nearly identical
  - slight timing differences
  - score changes state/inputs
- On average
  - scores over 469,209!
  - solves 29 levels!
- Sticky action eval:
  - scores 281,264
  - level 18

Results with Robust Deep Neural Networks



- Increased Gym's time limits
- Best neural network
  - scores over 4 million
  - reaches level 295
- Beats human world record
  - 1,219,200
  - achieves strictest definition of "super-human"

Results with Robust Deep Neural Networks



- Even beats previous work from human demonstrations
  - better demos
  - more demos

Not Expensive!

- Solving Level 1 of Montezuma's Revenge
  - Phase 1: Exploration
    - ~1 hour!
    - single machine (22 CPUs, 50GB RAM)
    - runs produce ~4GB of data
  - Phase 2: Robustification
    - ~1 day
      - 16 GPUS
- All told: ~1 day on modest hardware
  - compare to billions of frames, thousands of workers

Similar to graph search? (e.g. breadth-first search)

- Yes, but

1. Go-Explore adds Phase 2: Robustification to handle noise
2. Such algorithms are intractable in raw high-D state space

Similar to graph search? (e.g. breadth-first search)

- Yes, but

1. Go-Explore adds Phase 2: Robustification to handle noise
2. Such algorithms are intractable in raw high-D state space
   - Go-Explore insight: run these great graph search algorithms in low-D conflated spaces!
   - adds many challenges
     - which cells can you reach from current cell? how (have to search)? can't replace subpaths. etc.
   - requires many algorithmic innovations
   - new research area: porting classic graph algorithms to high-D (conflated representations): BFS, DFS, Dijkstra's, A-Star, etc.