

# TAAC: Temporally Abstract Actor-Critic for Continuous Control

*Haonan Yu, Wei Xu, and Haichao Zhang*  
Horizon Robotics



# Motivation: temporal abstraction (TA)

Temporally correlated actions



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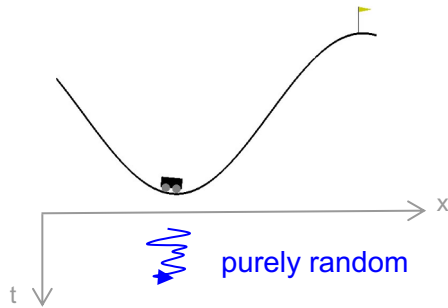
1. Temporally persistent exploration



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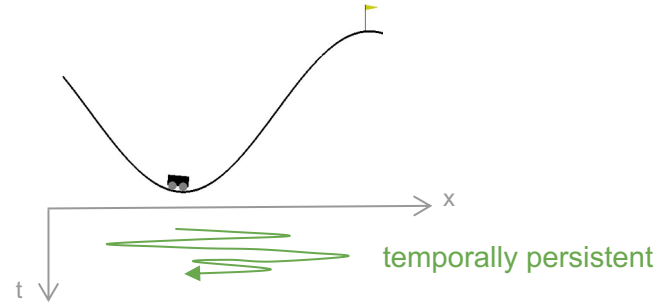
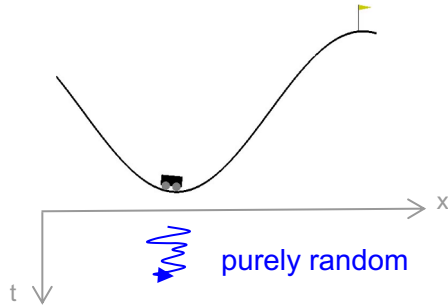
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## Temporally correlated actions

### 1. Temporally persistent exploration



Moving out of the valley more easily!



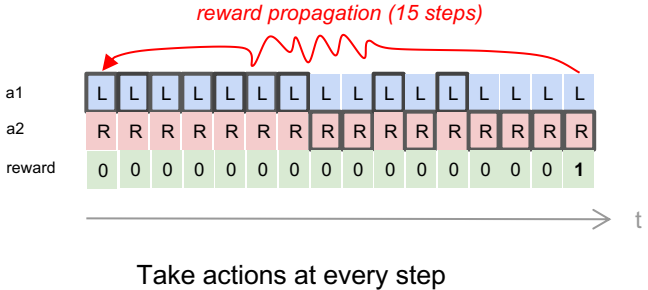
# Motivation: temporal abstraction (TA)

2. Better credit assignment with delayed reward (shorter horizon)



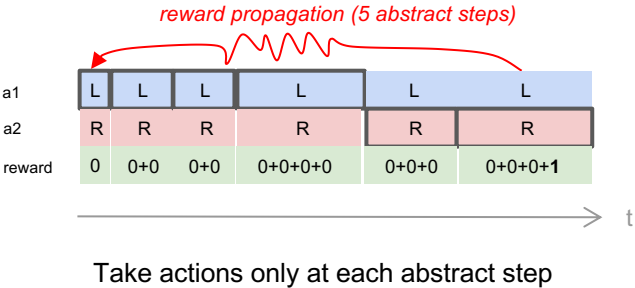
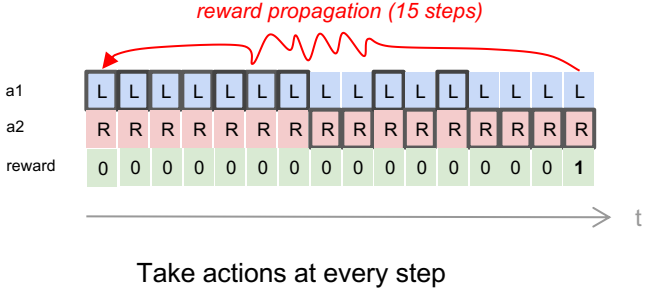
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Action repetition: perhaps the simplest temporal abstraction technique.



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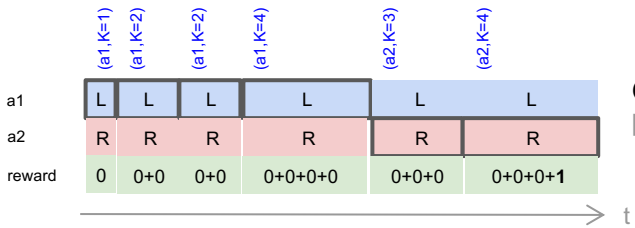
***Key questions:*** *what action to repeat & how long to repeat it?*



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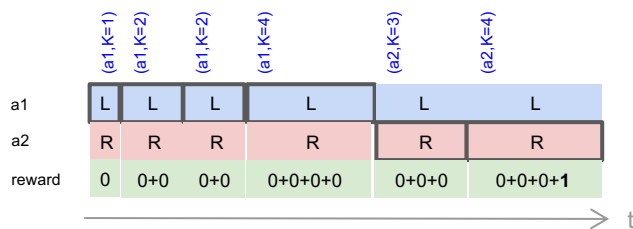
Open-loop methods output an action and its duration at once  
[Sharma et al., 2017] [Biedenkapp et al., 2021] [Dabney et al., 2021]



# Open-loop vs. closed-loop repetition

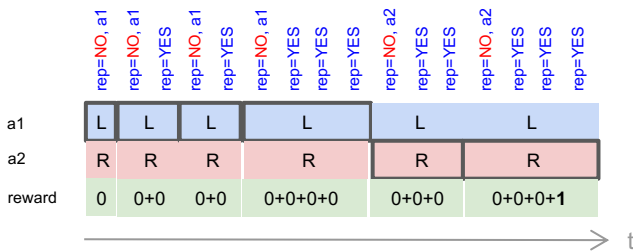
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Closed-loop methods decide “act-or-repeat” at every step

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# Temporally abstract actor-critic (TAAC)

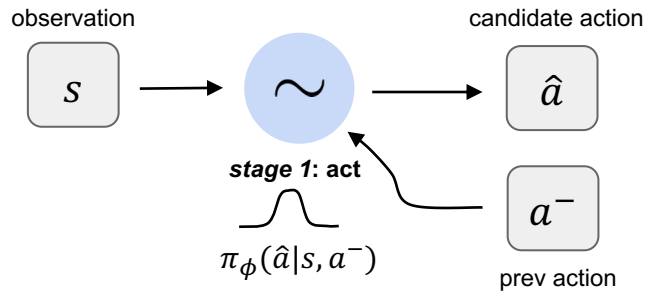
TAAC incorporates closed-loop action repetition into off-policy actor-critic for continuous control



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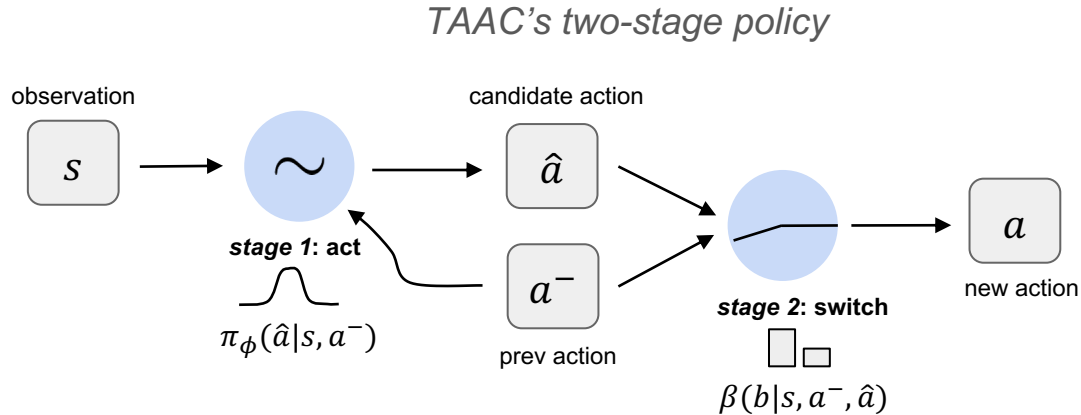
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*TAAC's two-stage policy*



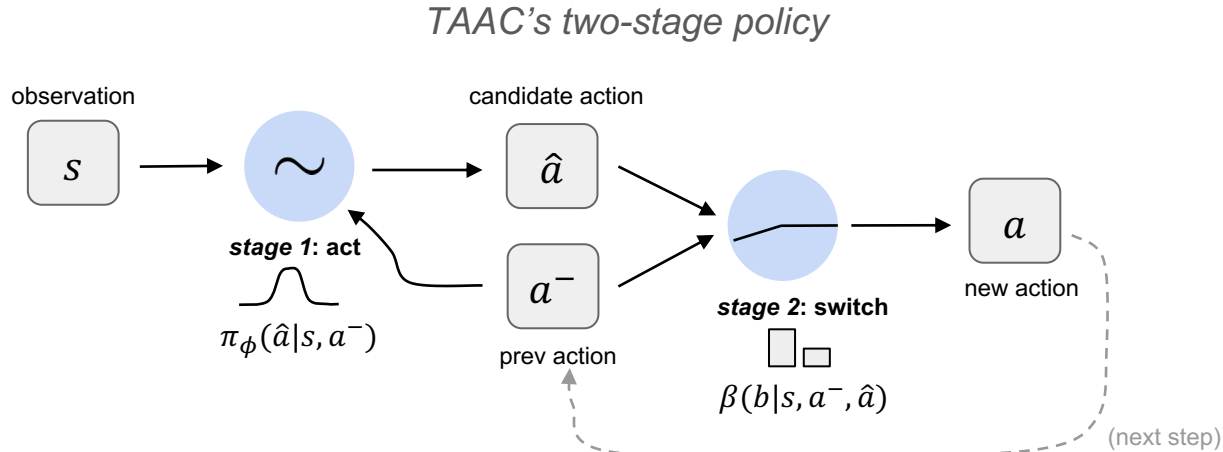
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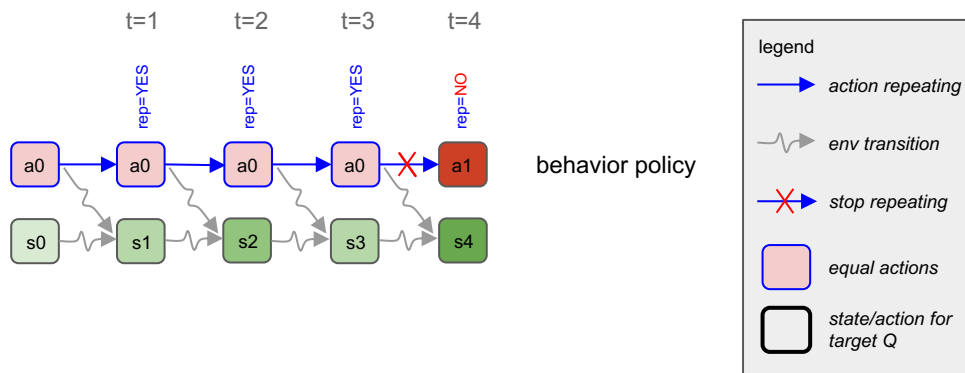
# Policy evaluation

A novel compare-through operator for multi-step TD backup



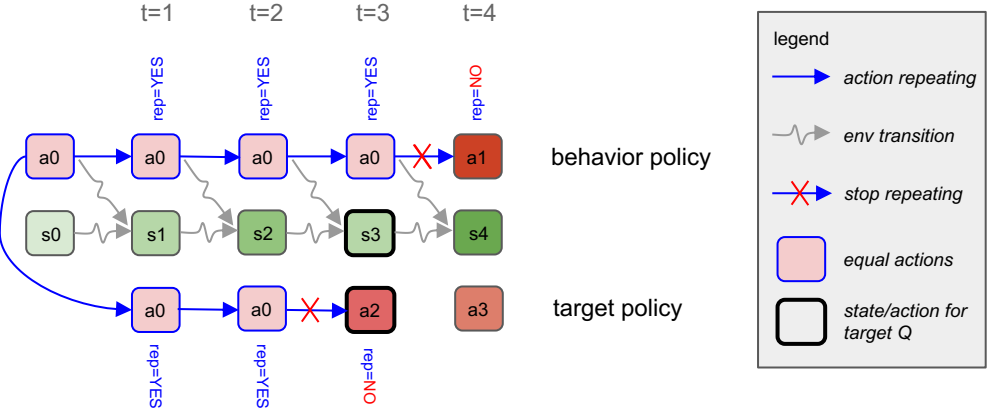
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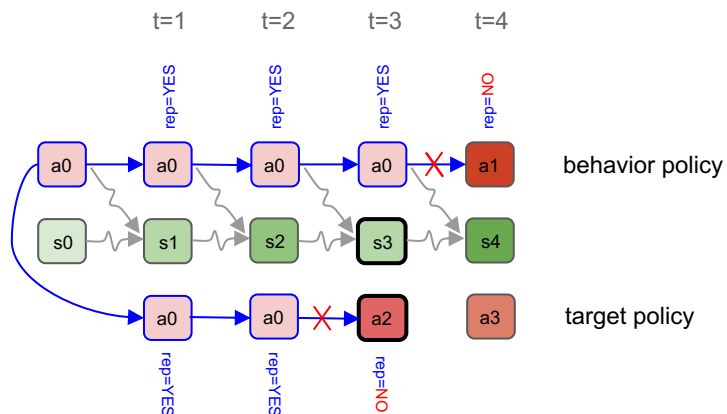
## A novel compare-through operator for multi-step TD backup



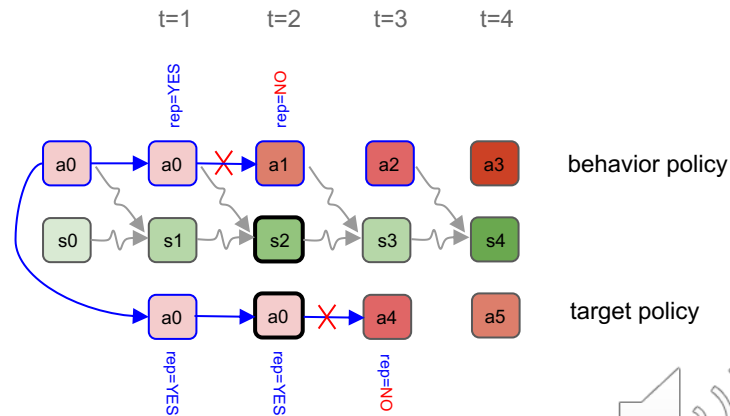
Example 1: We use  $Q(s_3, a_2)$  as the target to bootstrap  $Q(s_0, a_0)$  (3-step TD)

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Example 2: We use  $Q(s_2, a_0)$  as the target to bootstrap  $Q(s_0, a_0)$  (2-step TD)



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$$\beta(0)^* = \exp\left(\frac{Q(s, a^-)}{\alpha}\right) / Z(s) \quad \beta(1)^* = \exp\left(\frac{Q(s, \hat{a})}{\alpha}\right) / Z(s)$$



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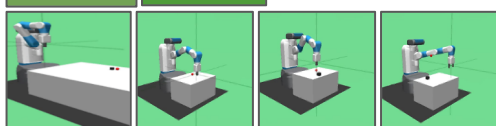
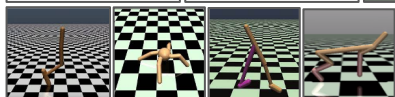
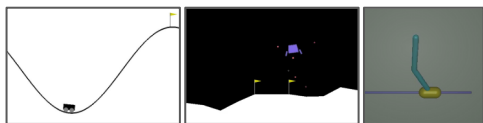
The actor  $\pi_\phi(\hat{a}|s, a^-)$  is trained similarly as in DDPG [Lillicrap et al., 2016] and SAC

[Haarnoja et al., 2018]:  $\frac{\partial Q(s, \hat{a})}{\partial \phi} \beta^*(1)$  (this is a good approximation to the full gradient)



# Tasks

5 categories of 14 continuous control tasks (13 standard; 1 customized)



Category	Task	Gym environment name	Observation space	Action space
<b>SimpleControl</b>	<i>MountainCarContinuous</i>	MountainCarContinuous-v0	$\mathbb{R}^2$	$[-1, 1]^1$
	<i>LunarLanderContinuous</i>	LunarLanderContinuous-v2	$\mathbb{R}^8$	$[-1, 1]^2$
	<i>InvertedDoublePendulum</i>	InvertedDoublePendulum-v2	$\mathbb{R}^{11}$	$[-1, 1]^1$
<b>Locomotion</b>	<i>Hopper</i>	Hopper-v2	$\mathbb{R}^{11}$	$[-1, 1]^3$
	<i>Ant</i>	Ant-v2	$\mathbb{R}^{111}$	$[-1, 1]^8$
	<i>Walker2d</i> <i>HalfCheetah</i>	Walker2d-v2 HalfCheetah-v2	$\mathbb{R}^{17}$	$[-1, 1]^6$
<b>Terrain</b>	<i>BipedalWalker</i>	BipedalWalker-v2	$\mathbb{R}^{24}$	$[-1, 1]^4$
	<i>BipedalWalkerHardcore</i>	BipedalWalkerHardcore-v2		
<b>Manipulation</b>	<i>FetchReach</i>	FetchReach-v1	$\mathbb{R}^{13}$	$[-1, 1]^4$
	<i>FetchPush</i>	FetchPush-v1	$\mathbb{R}^{28}$	
	<i>FetchSlide</i>	FetchSlide-v1		
	<i>FetchPickAndPlace</i>	FetchPickAndPlace-v1		
<b>Driving</b>	<i>Town01</i>	Town01	“camera”: $\mathbb{R}^{128 \times 64 \times 3}$ , “radar”: $\mathbb{R}^{200 \times 4}$ , “collision”: $\mathbb{R}^{4 \times 3}$ , “IMU”: $\mathbb{R}^7$ , “goal”: $\mathbb{R}^3$ , “velocity”: $\mathbb{R}^3$ , “navigation”: $\mathbb{R}^{8 \times 3}$ “prev action”: $[-1, 1]^4$	$[-1, 1]^4$





# Experiment results

## Comparison methods

SAC [Haarnoja et al., 2018]: flat RL

SAC-Ntd: SAC + Retrace [Munos et al., 2016] + N-TD

SAC-Nrep: SAC + Fixed action repetition

SAC-Krep: open-loop action repetition [Sharma et al., 2017;  
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SAC-EZ: SAC with EZ-greedy [Dabney et al., 2021]

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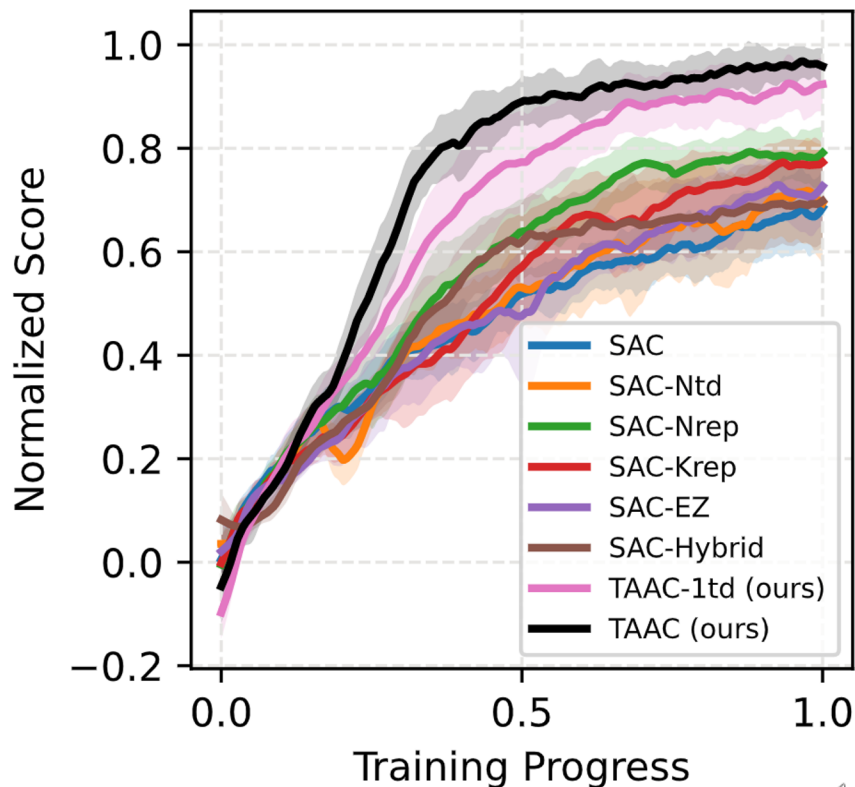
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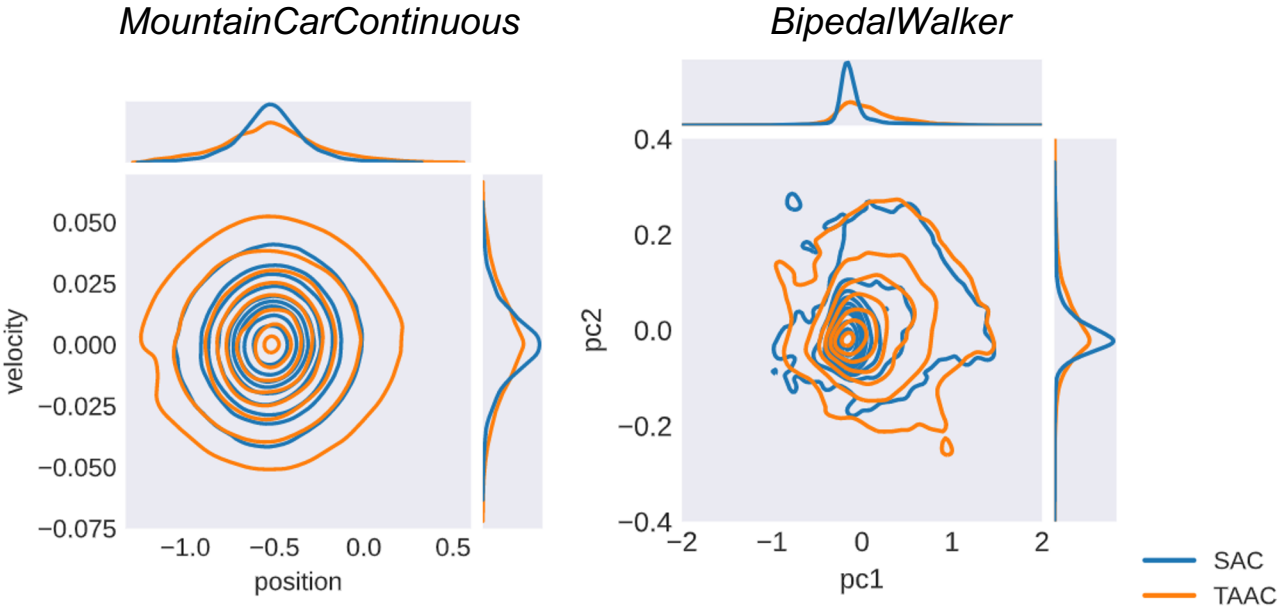
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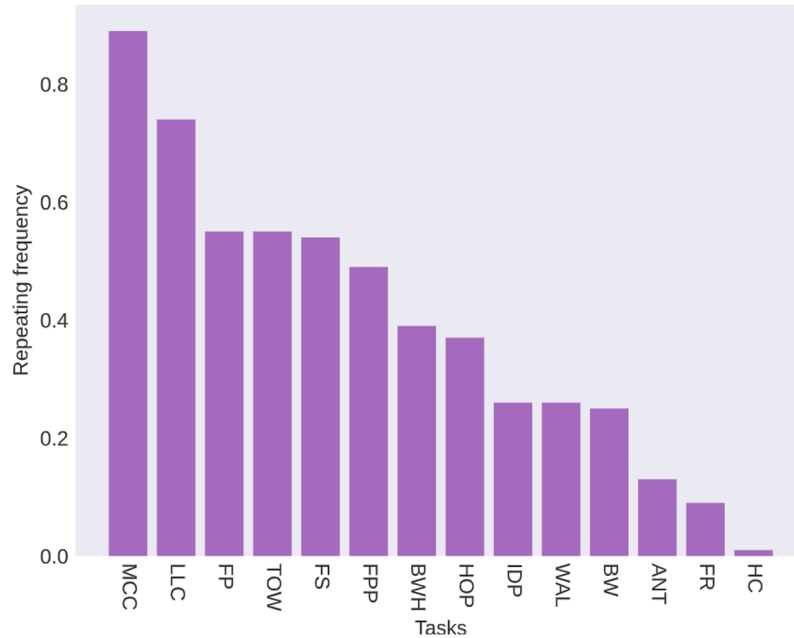
(Normalized and averaged over 14 tasks)

# Exploration behavior analysis



Random policies behaviors

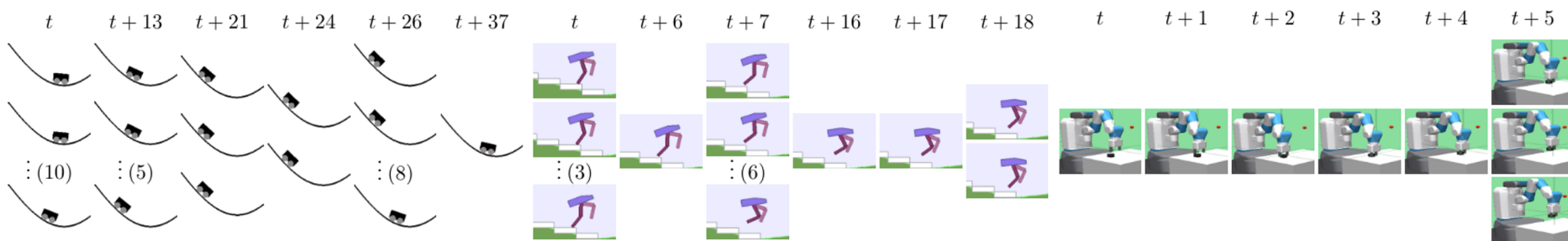
# Action repeating frequency



Evaluating a trained TAAC model  
for 100 episodes and calculating the repeating frequency



# Action repeating patterns



*Each column represents the same action*

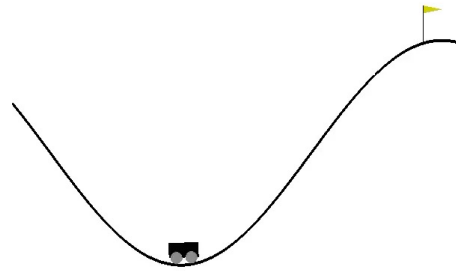
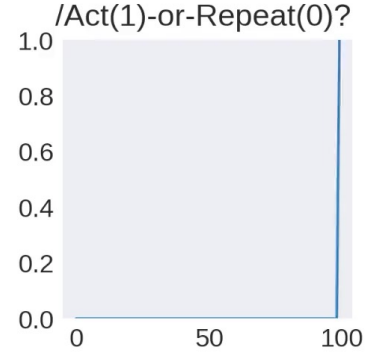
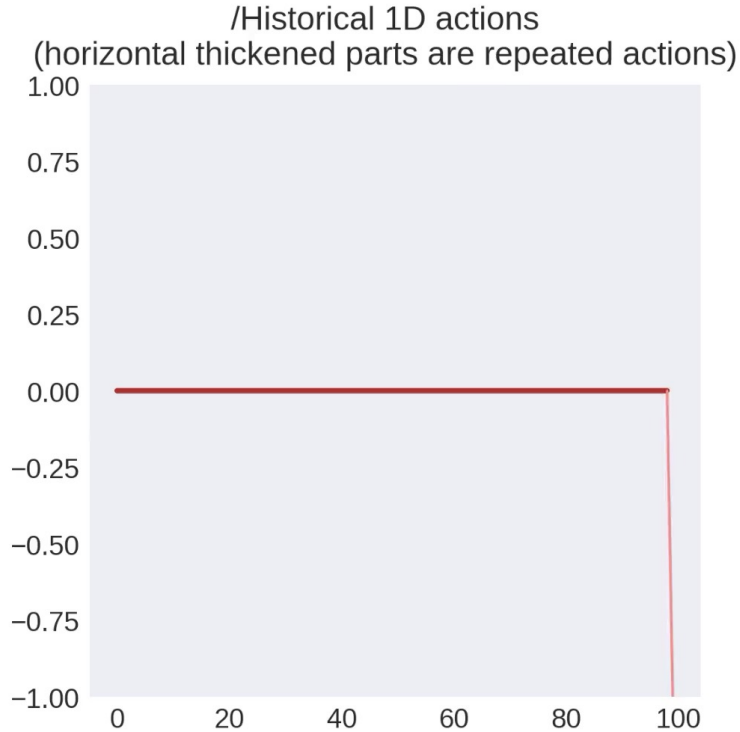
TAAC learns to skip learning to generate new actions at non-critical states, and save the actor network's representational power for critical states!



# Demos



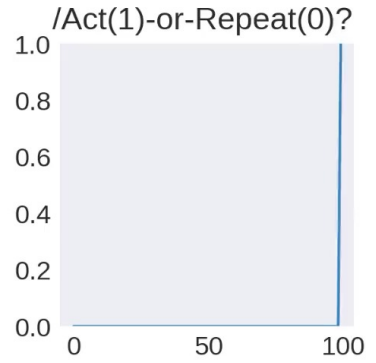
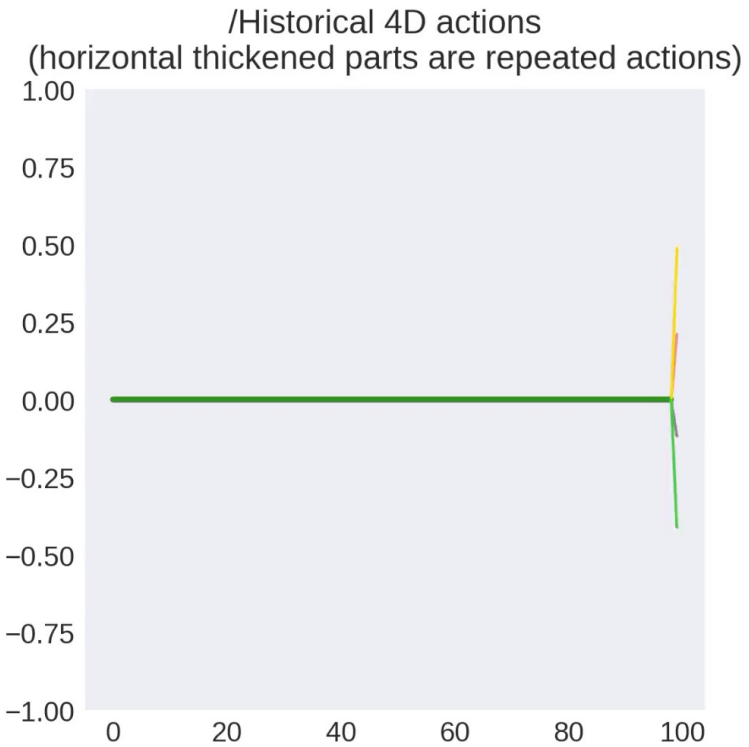
# Demo - MountainCarContinuous



(Played in 0.5x speed for a better view)



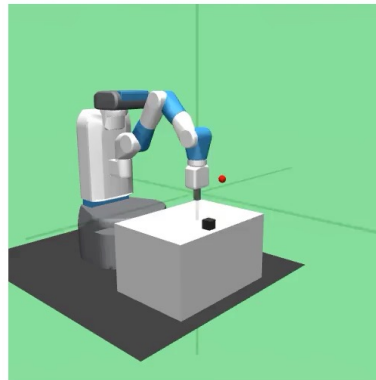
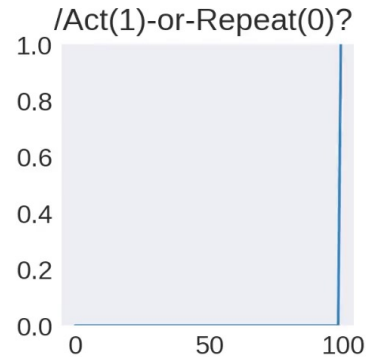
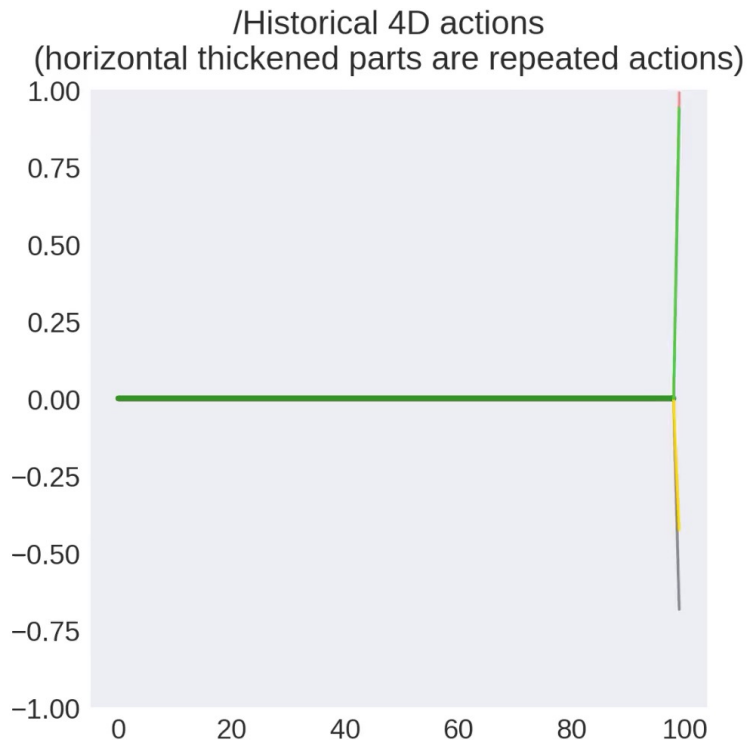
# Demo - *BipedalWalker*



(Played in 0.5x speed for a better view)



# Demo - *FetchPickAndPlace*



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Code: <https://github.com/hnyu/taac>

