Carnegie Mellon
School of Computer Science

Deep Reinforcement Learning and Control

Pathwise derivatives, DDPG, Multigoal RL

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Part of the slides on path wise derivatives adapted from John Schulman

Computing Gradients of Expectations

When the variable w.r.t. which we are differentiating appears in the distribution:

$$\nabla_\theta \mathbb{E}_{x\sim p(\cdot|\theta)} \mathrm{F}(x) = \boxed{\mathbb{E}_{x\sim p(\cdot|\theta)} \nabla_\theta \log p(\,\cdot\,|\,\theta) \mathrm{F}(x)} \quad \text{e.g.} \quad \nabla_\theta \mathbb{E}_{a\sim\pi_\theta} R(a, s)$$

likelihood ratio gradient estimator

When the variable w.r.t. which we are differentiating appears in the expectation:

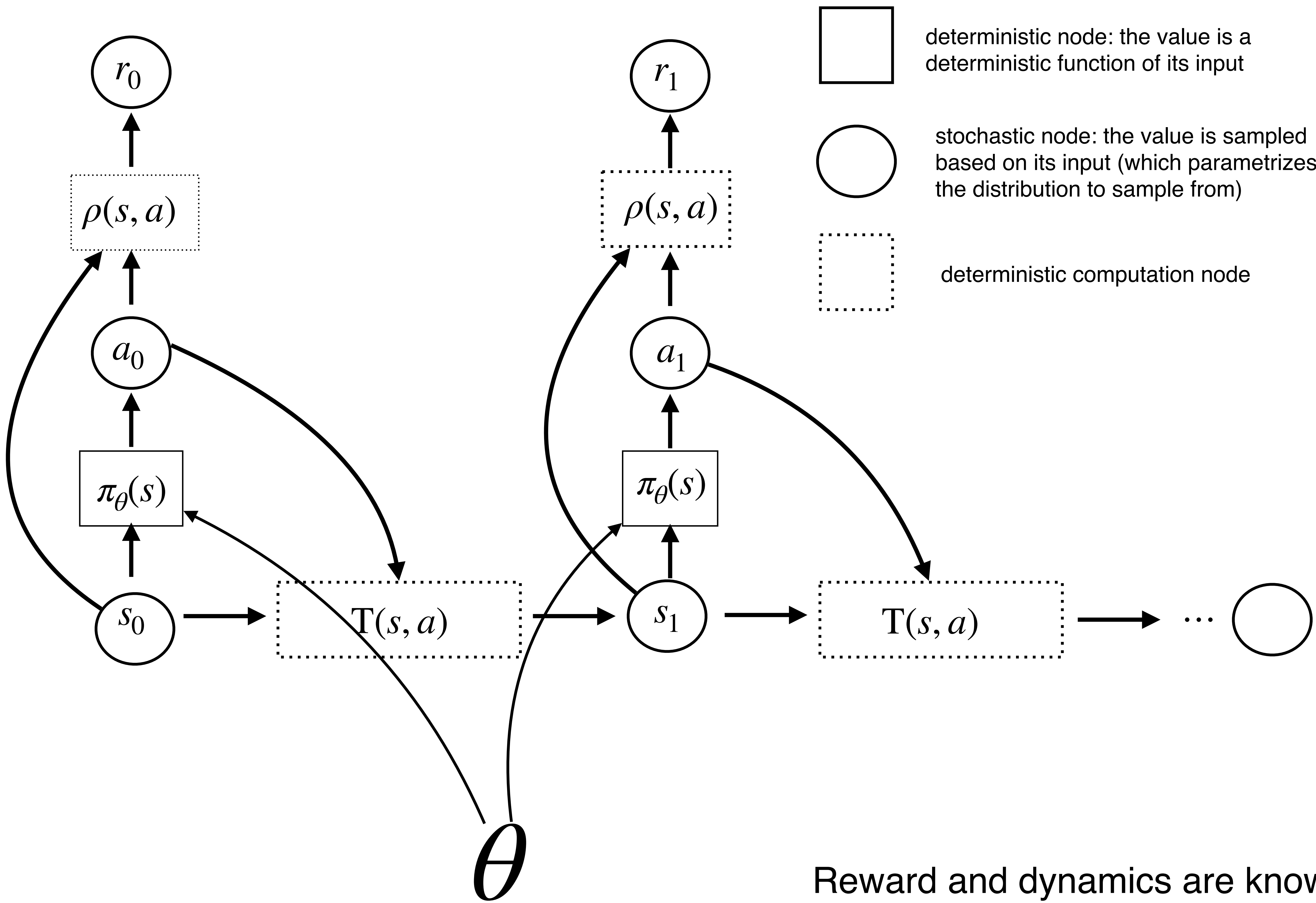
$$\nabla_\theta \mathbb{E}_{z\sim\mathcal{N}(0,1)} \mathrm{F}(x(\theta), z) = \mathbb{E}_{z\sim\mathcal{N}(0,1)} \nabla_\theta \mathrm{F}(x(\theta), z) = \boxed{\mathbb{E}_{z\sim\mathcal{N}(0,1)} \frac{d\mathrm{F}(x(\theta), z)}{dx} \frac{dx}{d\theta}}$$

pathwise derivative

Re-parametrization trick: For some distributions p(xl\theta) we can switch from one gradient estimator to the other.

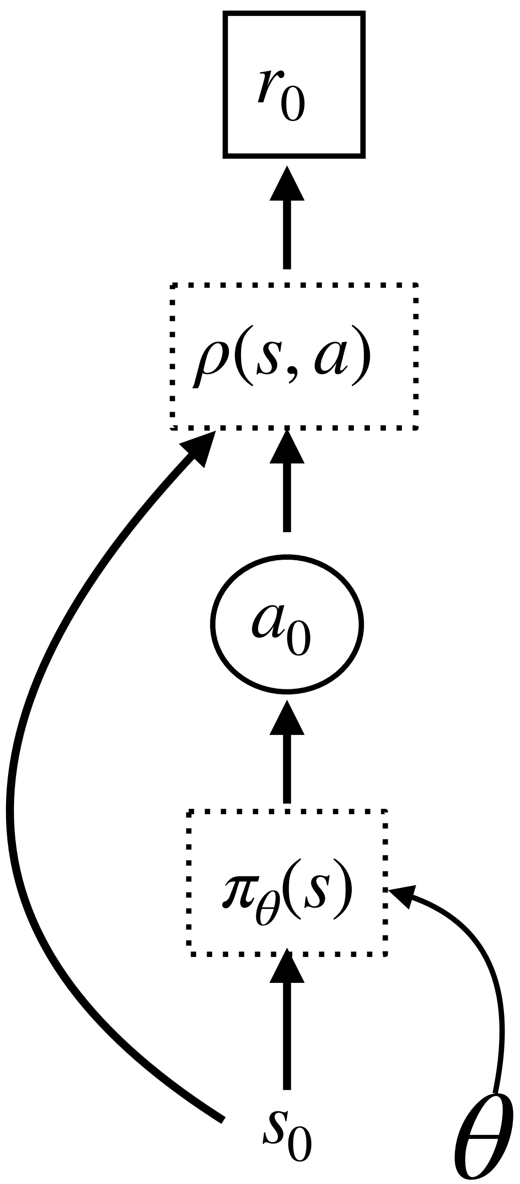
Why would we want to do so?

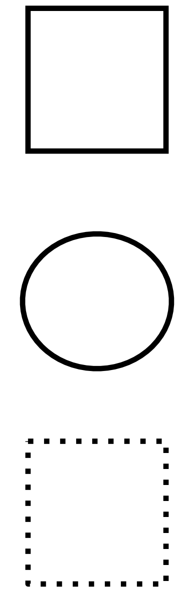
Known MDP



Reward and dynamics are known

Known MDP-let's make it simpler





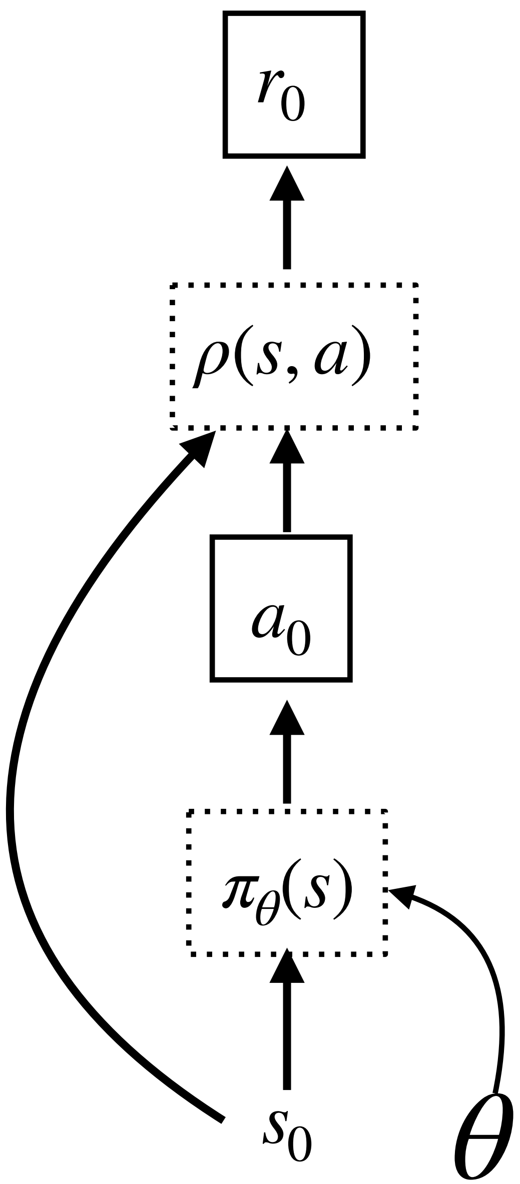
deterministic node: the value is a deterministic function of its input

stochastic node: the value is sampled based on its input (which parametrizes the distribution to sample from)

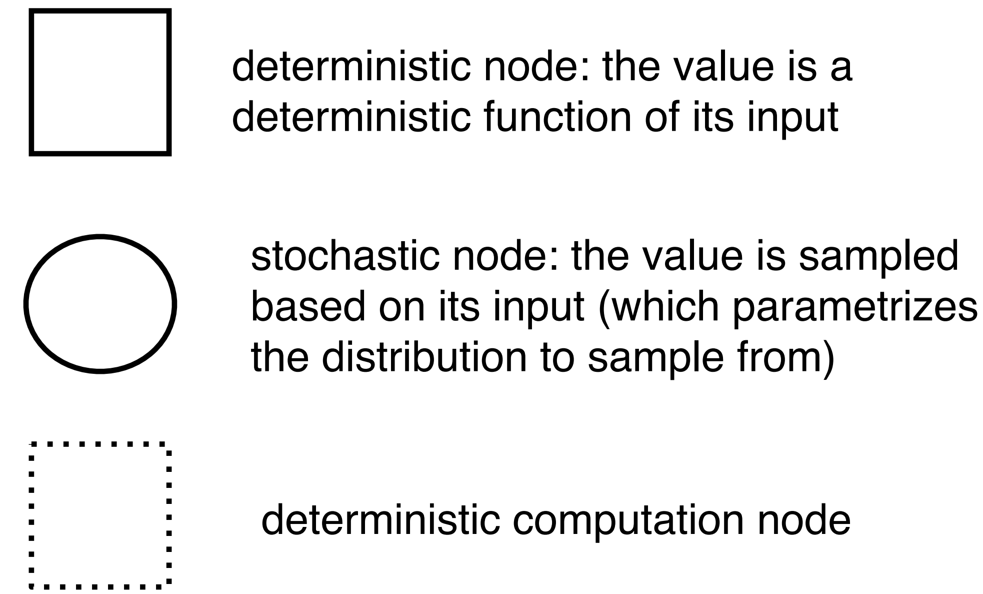
deterministic computation node

I want to learn \theta to maximize the reward obtained.

What if the policy is deterministic?



$$a = \pi_\theta(s)$$

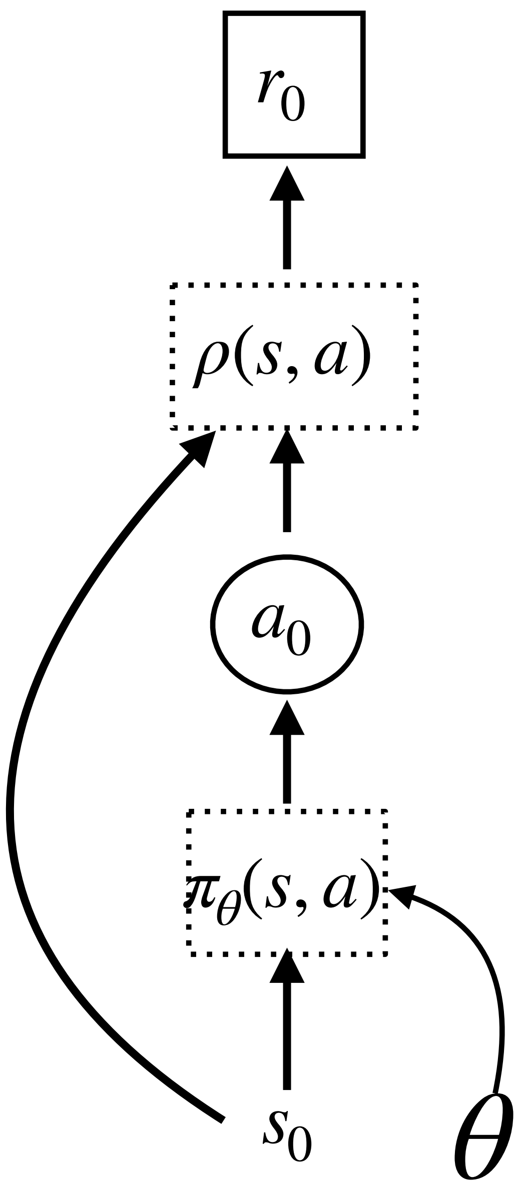


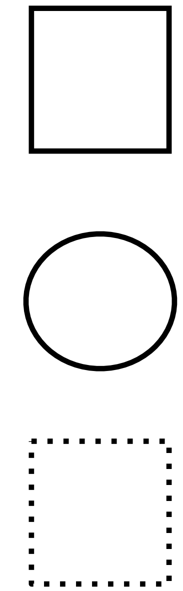
I want to learn \theta to maximize the reward obtained.

I can compute the gradient with backpropagation.

$$\nabla_\theta \rho(s, a) = \rho_a \pi_{\theta_\theta}$$

What if the policy is stochastic?





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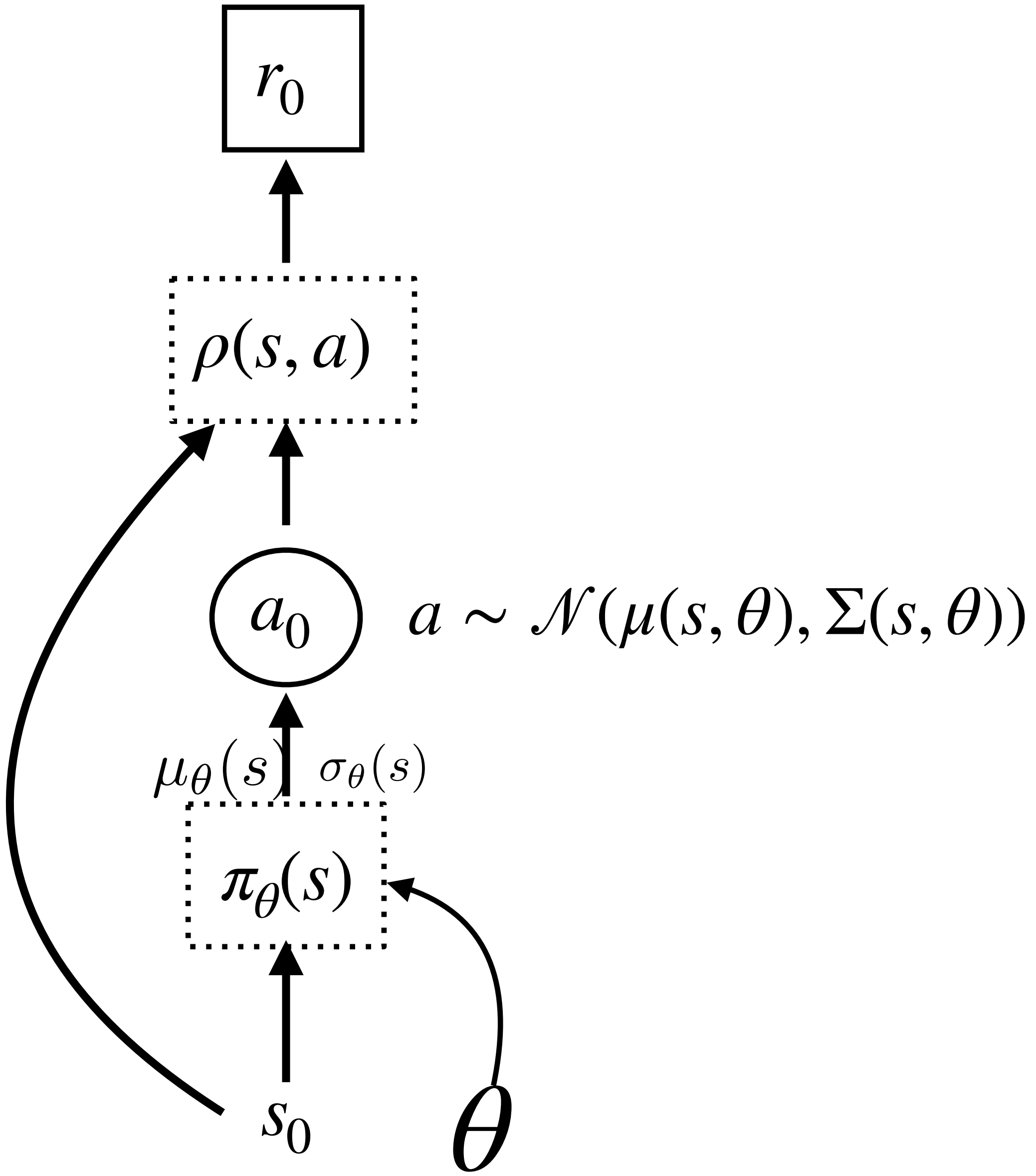
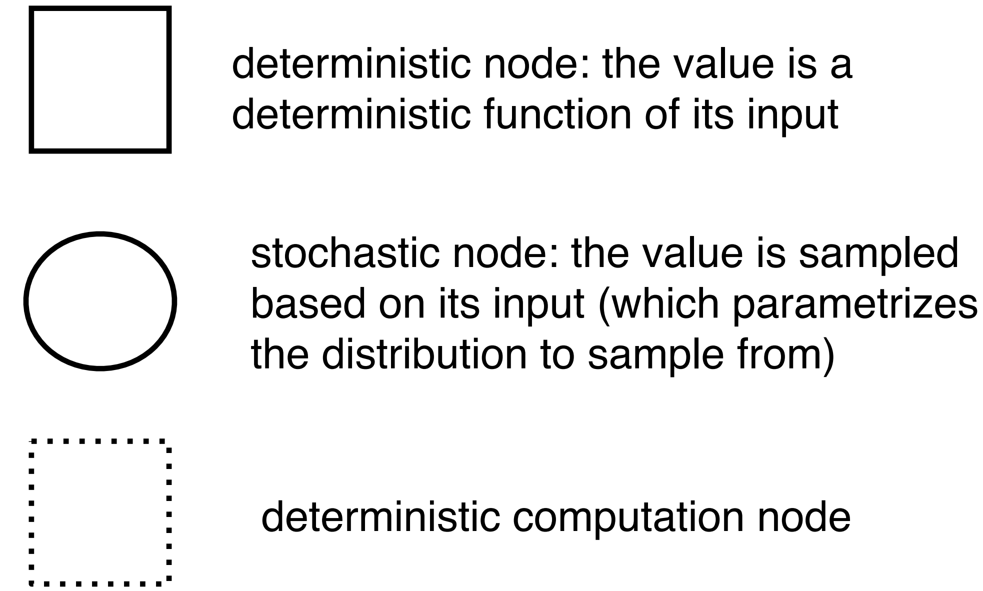
Likelihood ratio estimator, works for both continuous and discrete actions

$$\boxed{\mathbb{E}_a \nabla_\theta \log \pi_\theta(s,a)\rho(s,a)}$$

Policies are parametrized Gaussians





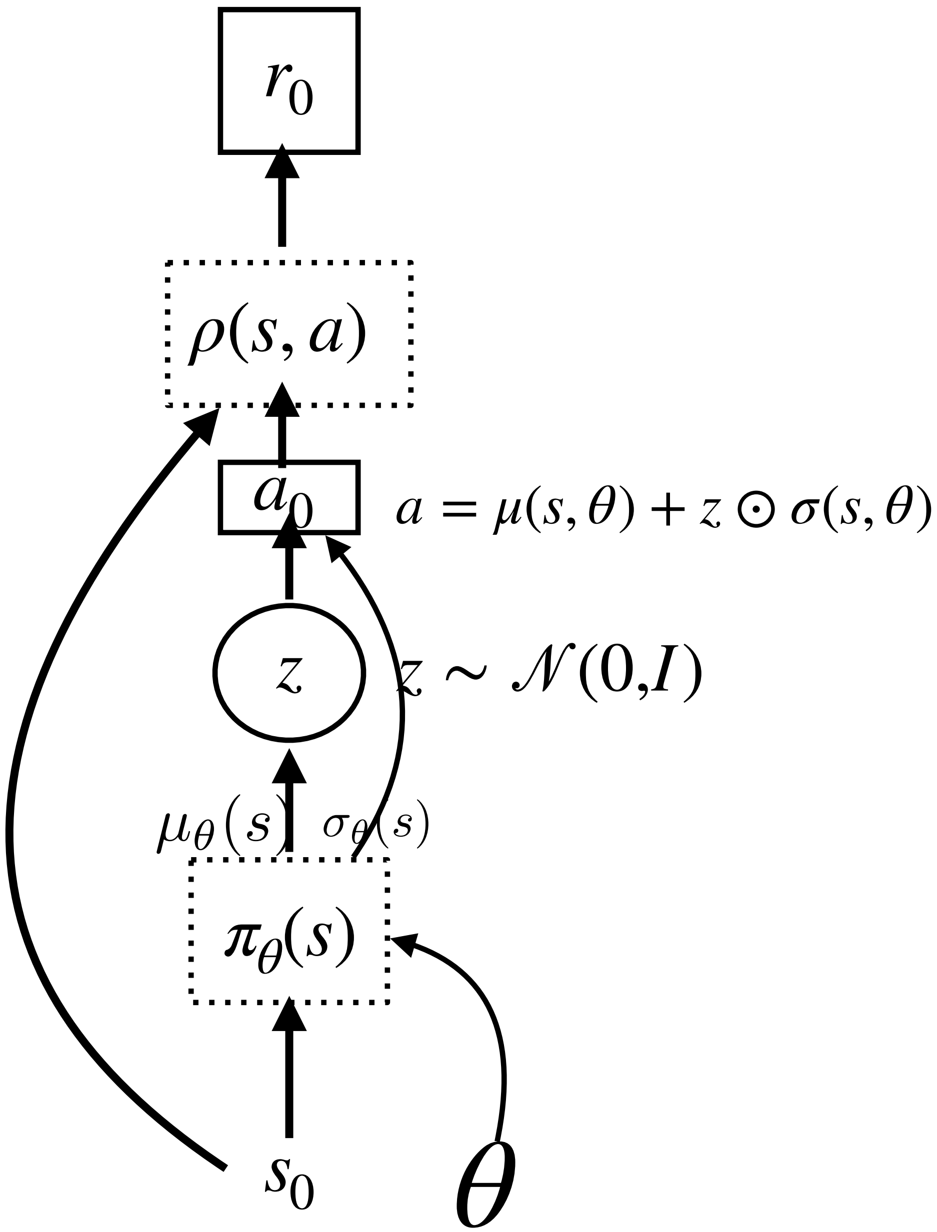
I want to learn \theta to maximize the reward obtained.

$$\boxed{\mathbb{E}_a \nabla_\theta \log \pi_\theta(s,a)\rho(s,a)}$$

If σ^2 is constant:

$$\nabla_\theta \log \pi_\theta(s,a) = \frac{(a-\mu(s;\theta))\frac{\partial \mu(s;\theta)}{\partial \theta}}{\sigma^2}$$

Re-parametrization for Gaussian



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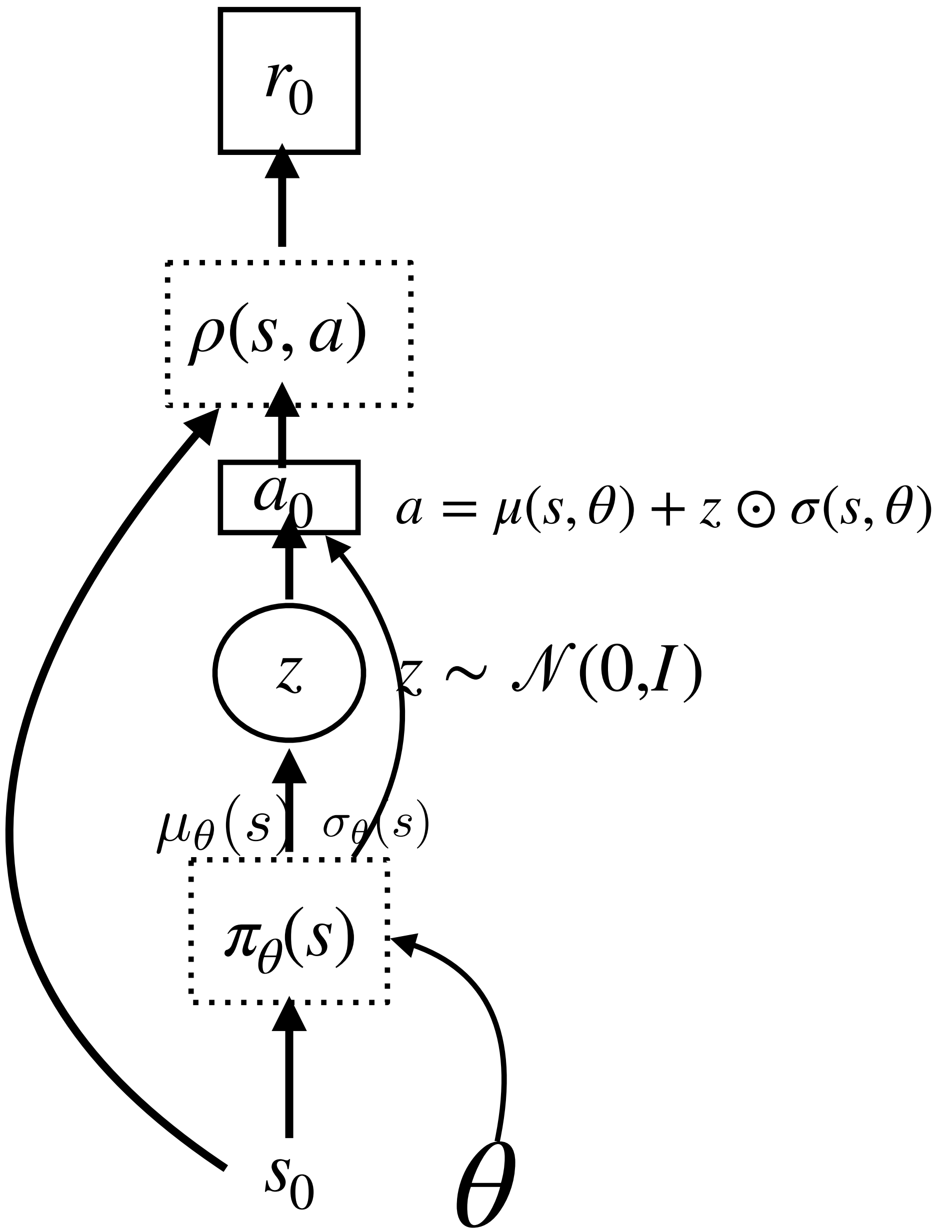

$$\mathbb{E}(\mu + z\sigma) = \mu$$

$$\mathrm{Var}(\mu + z\sigma) = \sigma^2$$

isotropic

$$a = \mu(s,\theta) + z \odot \sigma(s,\theta)$$

$$\frac{da}{d\theta} = \frac{d\mu(s,\theta)}{d\theta} + z \odot \frac{d\sigma(s,\theta)}{d\theta}$$

$$\nabla_\theta \mathbb{E}_z \left[\rho\left(a(\theta,z),s\right)\right] = \mathbb{E}_z \frac{d\rho\left(a(\theta,z),s\right)}{da}\frac{da(\theta,z)}{d\theta}$$

Sample estimate:

$$\nabla_\theta \frac{1}{N}\sum_{i=1}^{N}\left[\rho\left(a(\theta,z_i),s\right)\right] = \frac{1}{N}\sum_{i=1}^{N}\frac{d\rho\left(a(\theta,z),s\right)}{da}\frac{da(\theta,z)}{d\theta}\Big|_{z=z_i}$$

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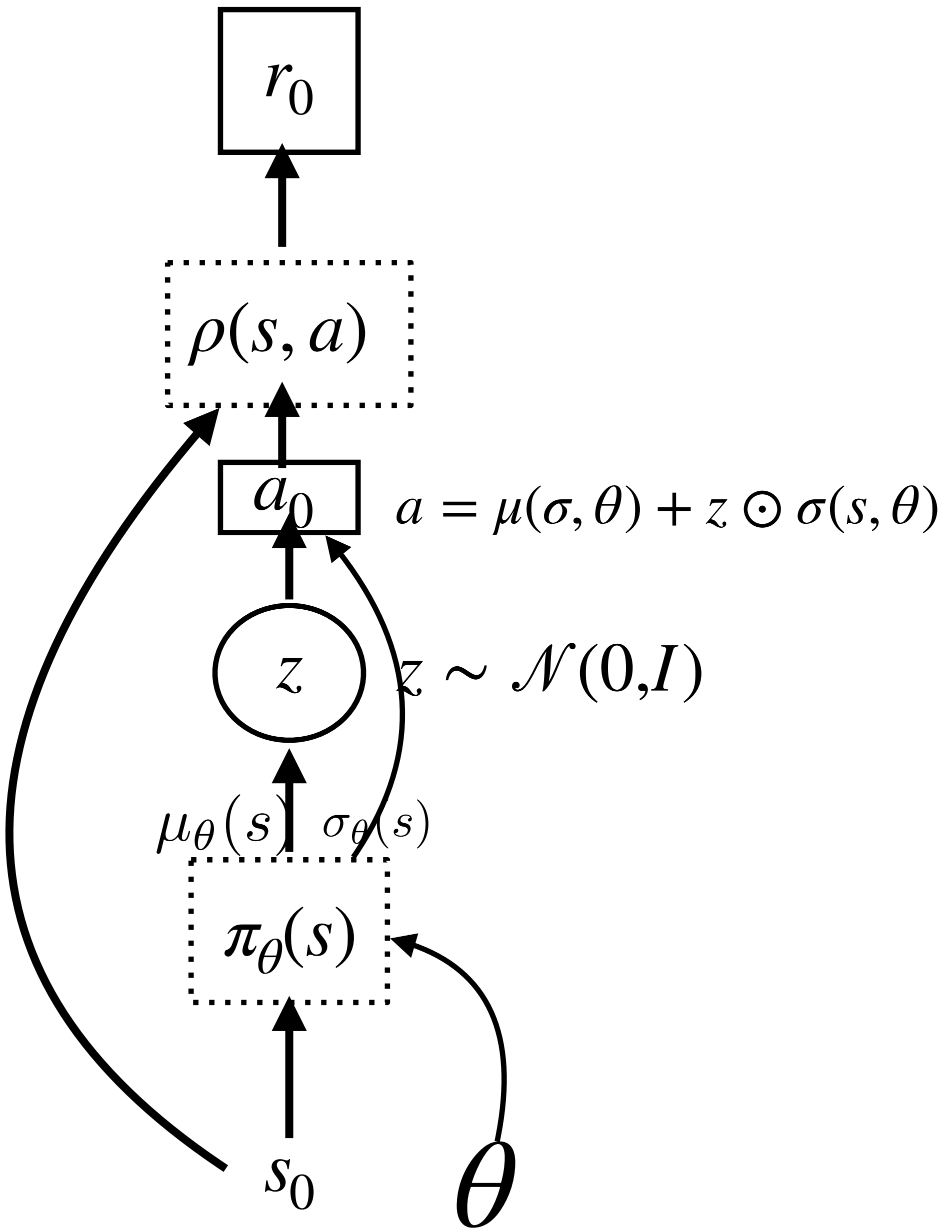

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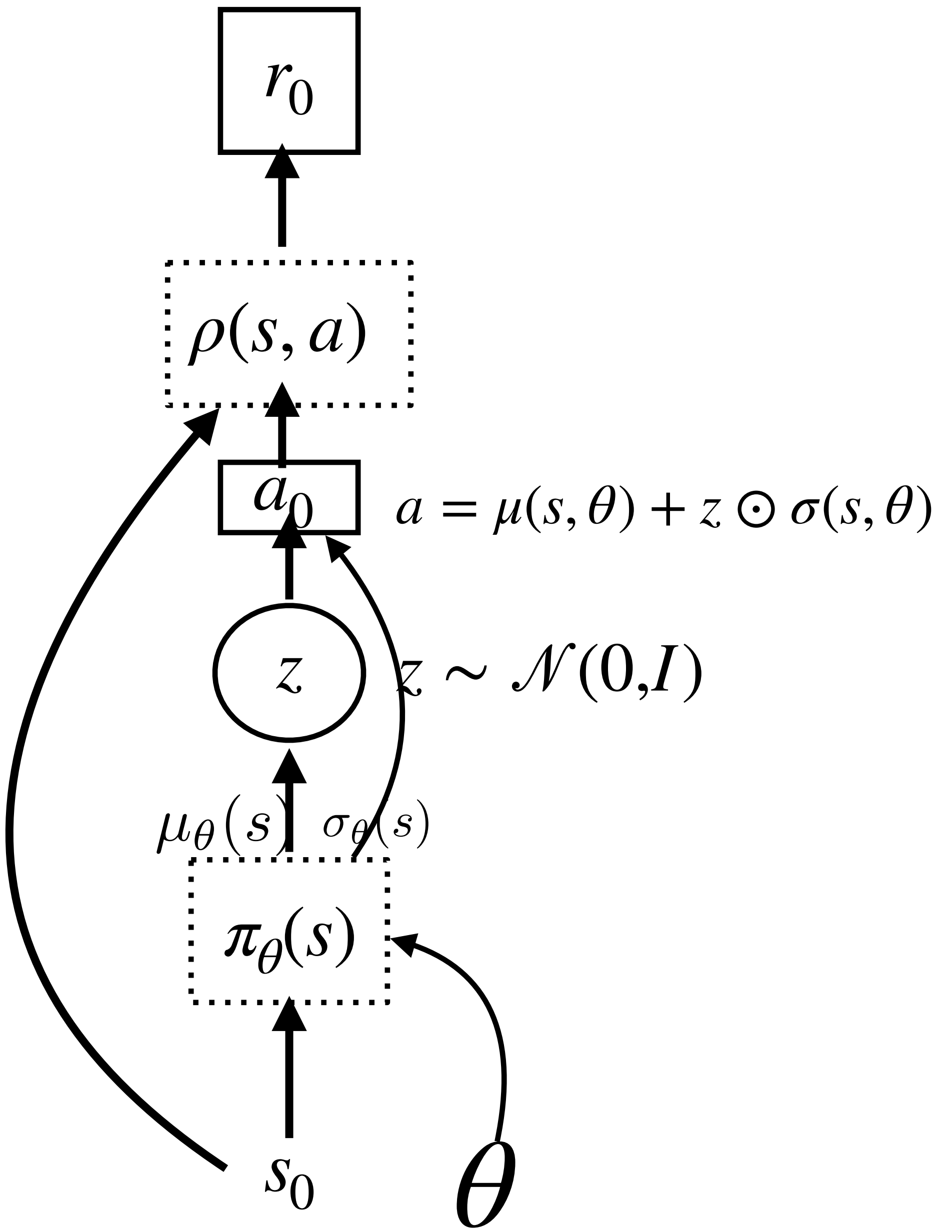

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general

$$a = \mu(\sigma,\theta) + Lz, \quad \Sigma = LL^\top$$

Likelihood ratio grad estimator:

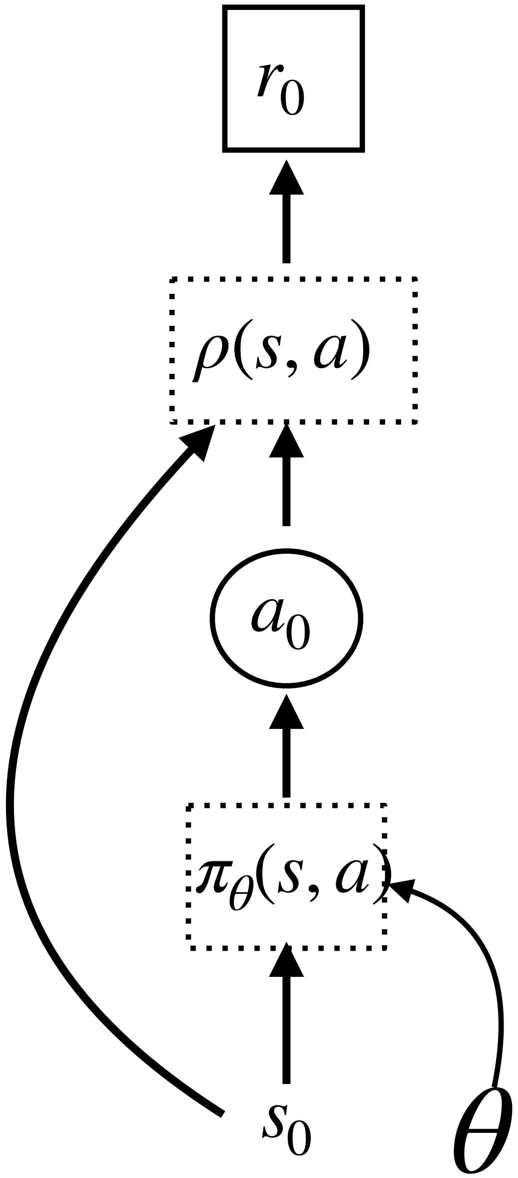
$$\boxed{\mathbb{E}_a \nabla_\theta \log \pi_\theta(s,a)\rho(s,a)}$$

Pathwise derivative:

$$\boxed{\mathbb{E}_z \frac{d\rho\left(a(\theta,z),s\right)}{da}\frac{da(\theta,z)}{d\theta}}$$

The pathwise derivative uses the derivative of the reward w.r.t. the action!

Policies are parametrized Categorical distr



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Re-parametrization for categorical distributions

Consider variable y following the K categorical distribution:

$$y_k \sim \frac{\exp((\log p_k)/\tau)}{\sum_{j=0}^{K} \exp((\log p_j)/\tau)}$$

Categorical reparametrization with Gumbel-Softmax, Sang et al. 2017

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Re-parametrization:

$$a_k = \arg\max_k(\log p_k + \epsilon_k), \quad \epsilon_k = -\log(-\log(U)), \quad u \sim \mathcal{U}[0,1]$$

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In the forward pass you sample from the parametrized distribution

$$a_k \sim G(\log p)$$

In the backward pass you use the soft distribution:

$$\frac{da}{d\theta} = \frac{dG}{dp}\frac{dp}{d\theta}$$

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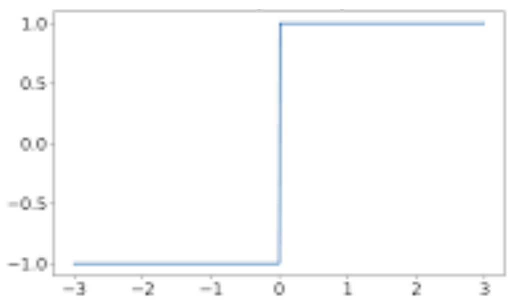
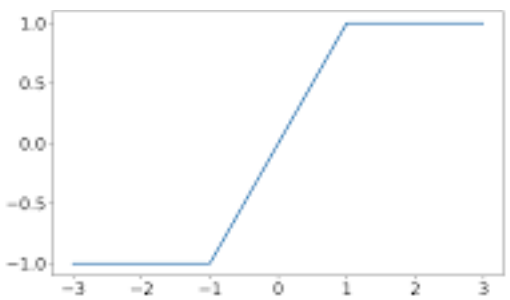
Back-propagating through discrete variables

For binary neurons:

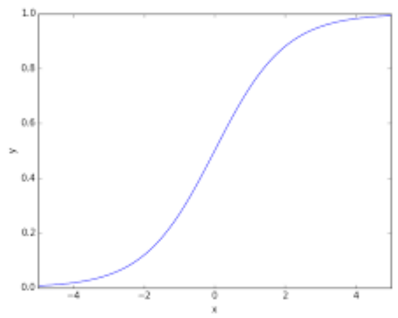
forward pass



backward pass



Straight-through

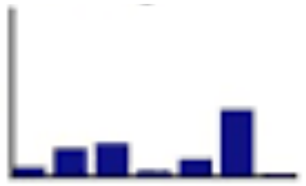


sigmoidal

For general categorically distributed neurons:

forward pass

backward pass



http://r2rt.com/binary-stochastic-neurons-in-tensorflow.html

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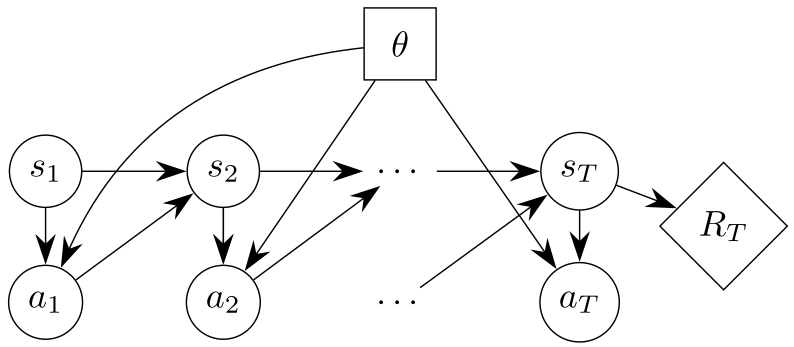
Re-parametrized Policy Gradients

- Episodic MDP:



We want to compute: $\nabla_\theta \mathbb{E}[R_T]$

Re-parametrized Policy Gradients

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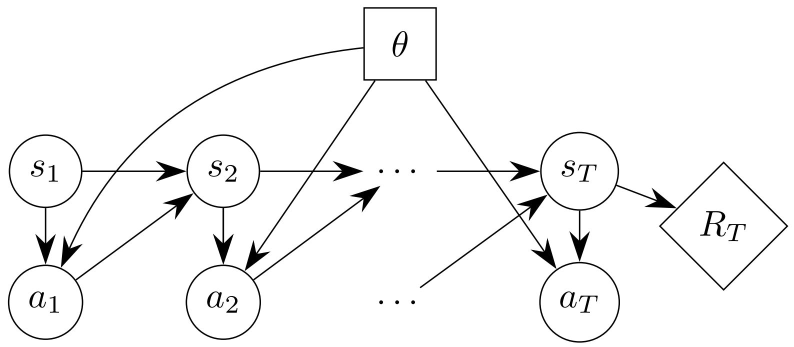
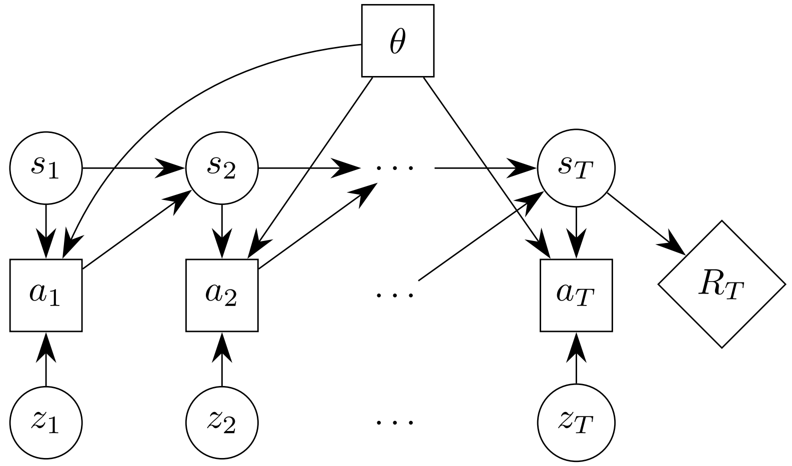


We want to compute: $\nabla_\theta \mathbb{E}[R_T]$

- Reparameterize: $a_t = \pi(s_t, z_t; \theta)$. z_t is noise from fixed distribution.



Re-parametrized Policy Gradients

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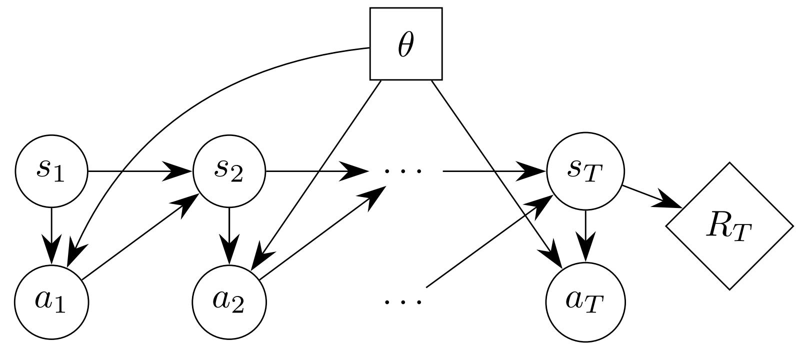

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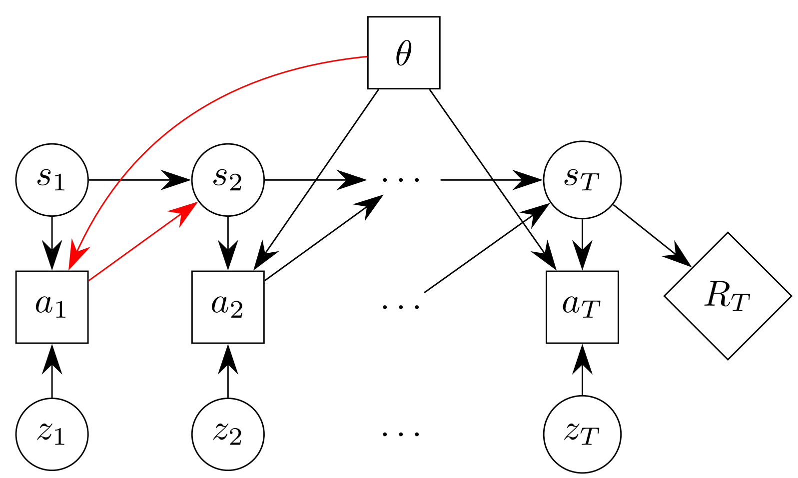
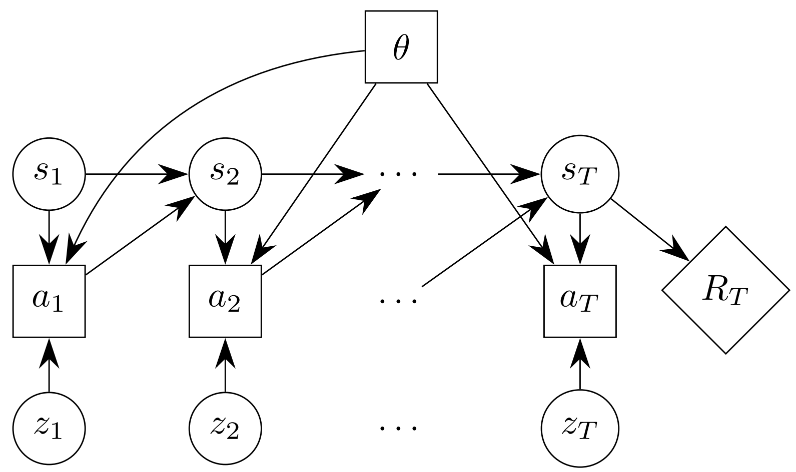


For path wise derivative to work, we need transition dynamics and reward function to be known.

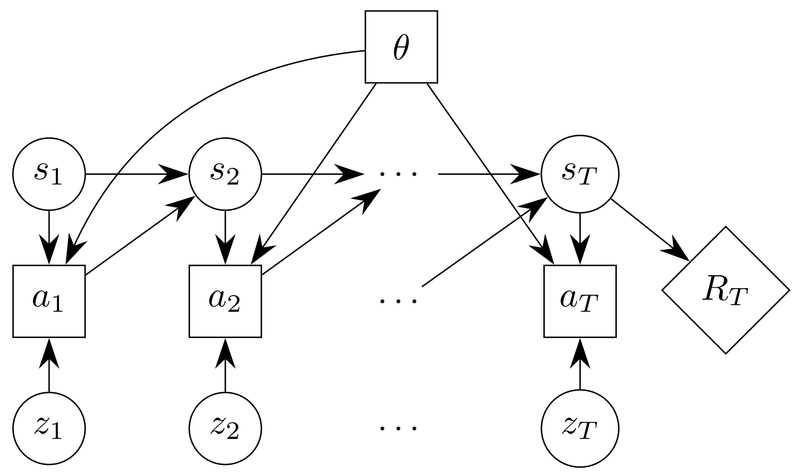
Re-parametrized Policy Gradients



$$\frac{\mathrm{d}}{\mathrm{d}\theta}\mathbb{E}\left[R_T\right] = \mathbb{E}\left[\sum_{t=1}^{T}\frac{\mathrm{d}R_T}{\mathrm{d}a_t}\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right] = \mathbb{E}\left[\sum_{t=1}^{T}\frac{\mathrm{d}}{\mathrm{d}a_t}\mathbb{E}\left[R_T \mid a_t\right]\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right]$$

For path wise derivative to work, we need transition dynamics and reward function to be known, or…

Re-parametrized Policy Gradients



$$
\begin{aligned}
\frac{\mathrm{d}}{\mathrm{d}\theta}\mathbb{E}\left[R_T\right] &= \mathbb{E}\left[\sum_{t=1}^{T} \frac{\mathrm{d}R_T}{\mathrm{d}a_t}\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right] = \mathbb{E}\left[\sum_{t=1}^{T} \frac{\mathrm{d}}{\mathrm{d}a_t}\mathbb{E}\left[R_T \mid a_t\right]\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right] \\
&= \mathbb{E}\left[\sum_{t=1}^{T} \frac{\mathrm{d}Q(s_t, a_t)}{\mathrm{d}a_t}\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right] = \mathbb{E}\left[\sum_{t=1}^{T} \frac{\mathrm{d}}{\mathrm{d}\theta}Q(s_t, \pi(s_t, z_t; \theta))\right]
\end{aligned}
$$

- Learn Q_ϕ to approximate $Q^{\pi,\gamma}$, and use it to compute gradient estimates.

N. Heess, G. Wayne, D. Silver, et al. "Learning continuous control policies by stochastic value gradients". In: *NIPS*. 2015

Stochastic Value Gradients V0

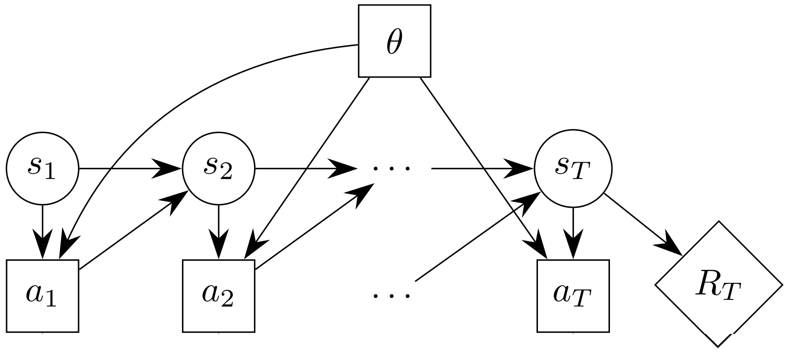
- Learn Q_ϕ to approximate $Q^{\pi,\gamma}$, and use it to compute gradient estimates.
- Pseudocode:

for iteration$=1, 2, \ldots$ **do**
  Execute policy π_θ to collect T timesteps of data
  Update π_θ using $g \propto \nabla_\theta \sum_{t=1}^{T} Q(s_t, \pi(s_t, z_t; \theta))$
  Update Q_ϕ using $g \propto \nabla_\phi \sum_{t=1}^{T} (Q_\phi(s_t, a_t) - \hat{Q}_t)^2$, e.g. with TD($\lambda$)
end for

What if we give up on stochastic actions?

N. Heess, G. Wayne, D. Silver, et al. "Learning continuous control policies by stochastic value gradients". In *NIPS*. 2015

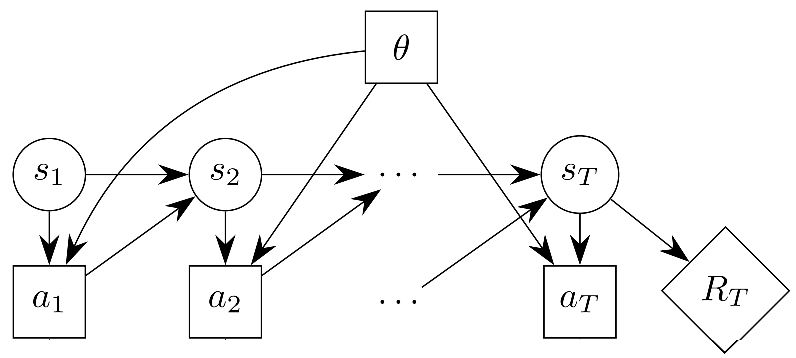
Deep Deterministic Policy Gradients



$$\frac{\mathrm{d}}{\mathrm{d}\theta}\mathbb{E}\left[R_T\right] = \mathbb{E}\left[\sum_{t=1}^{T} \frac{\mathrm{d}R_T}{\mathrm{d}a_t}\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right]$$

Continuous control with deep reinforcement learning, Lilicrap et al. 2016

Deep Deterministic Policy Gradients



This expectation refers to the dynamics after time t

$$\frac{\mathrm{d}}{\mathrm{d}\theta}\mathbb{E}\left[R_T\right] = \mathbb{E}\left[\sum_{t=1}^{T}\frac{\mathrm{d}R_T}{\mathrm{d}a_t}\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right] = \mathbb{E}\left[\sum_{t=1}^{T}\frac{\mathrm{d}}{\mathrm{d}a_t}\mathbb{E}\left[R_T \mid a_t\right]\frac{\mathrm{d}a_t}{\mathrm{d}\theta}\right]$$

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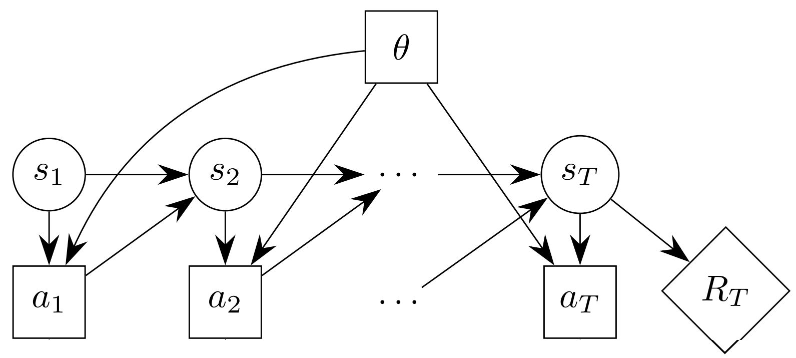

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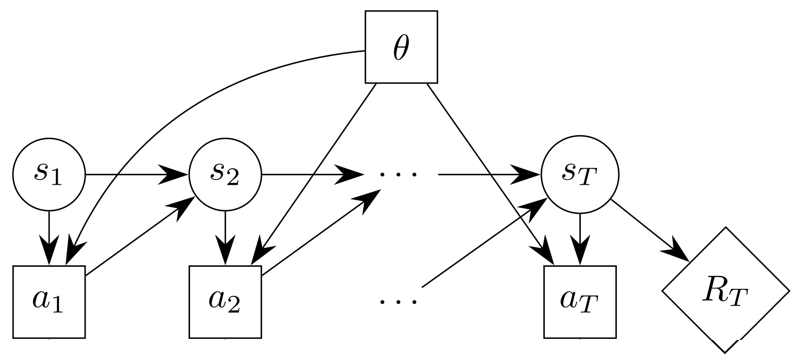

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Deep Deterministic Policy Gradients

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ.
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
  Initialize a random process $\mathcal{N}$ for action exploration
  Receive initial observation state s_1
  for t = 1, T **do**
    Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the current policy and exploration noise
    Execute action a_t and observe reward r_t and observe new state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in R
    Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
    Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu}\mu(s|\theta^\mu)|_{s_i}$$

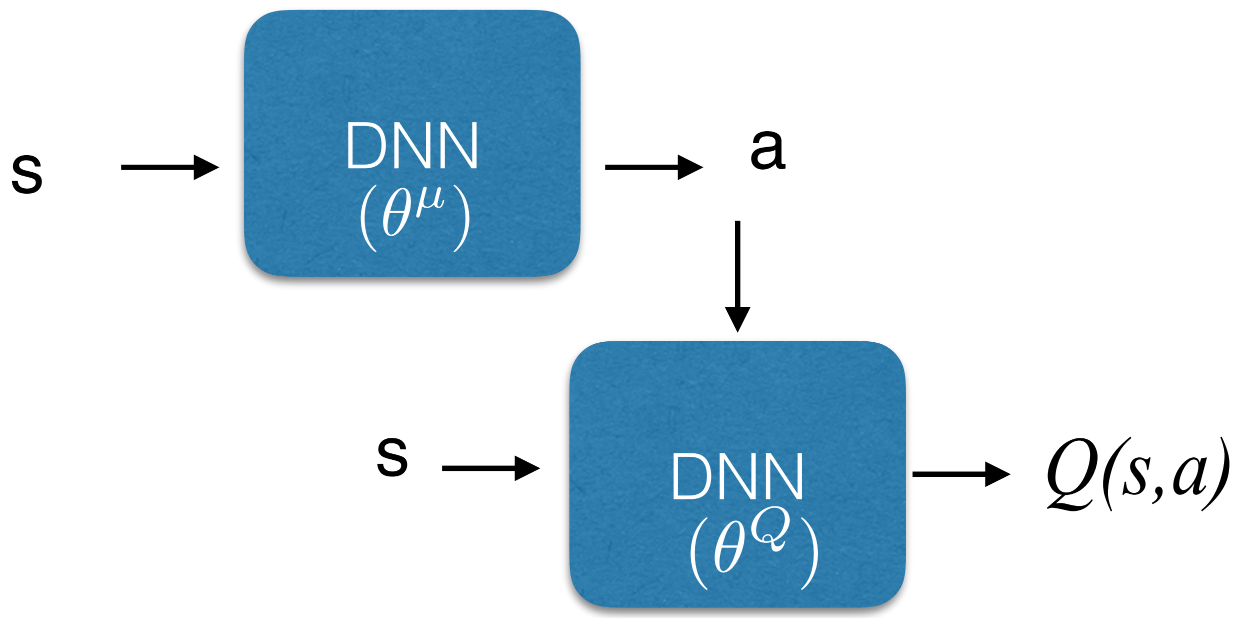
    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$
$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for
end for

Deep Deterministic Policy Gradients

$$a = \mu(\theta)$$

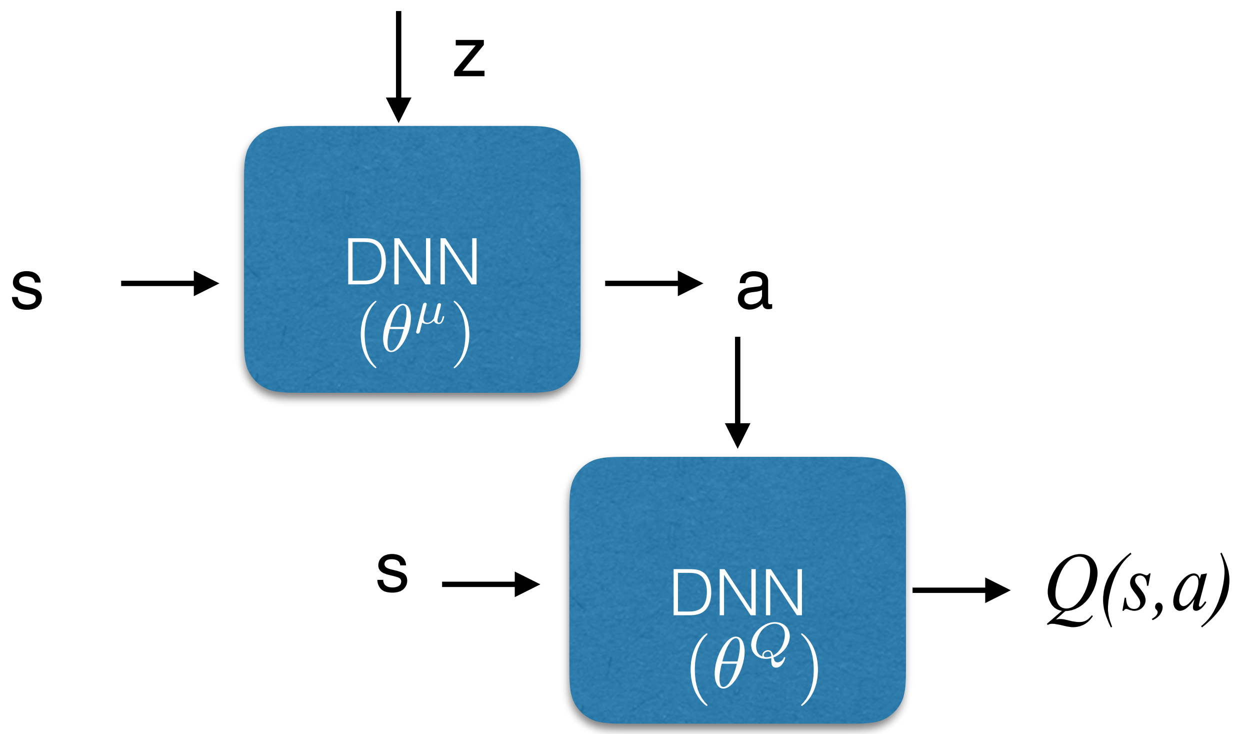


$$\nabla_{\theta^\mu} J \approx \mathbb{E}_{s_t \sim \rho^\beta} \left[\nabla_{\theta^\mu} Q(s, a|\theta^Q)|_{s=s_t, a=\mu(s_t|\theta^\mu)} \right]$$
$$= \mathbb{E}_{s_t \sim \rho^\beta} \left[\nabla_a Q(s, a|\theta^Q)|_{s=s_t, a=\mu(s_t)} \nabla_{\theta_\mu} \mu(s|\theta^\mu)|_{s=s_t} \right]$$

We are following a stochastic behavior policy to collect data.
Deep Q learning for contours actions-> DDPG

Stochastic Value Gradients V0

$$z \sim \mathcal{N}(0, 1)$$

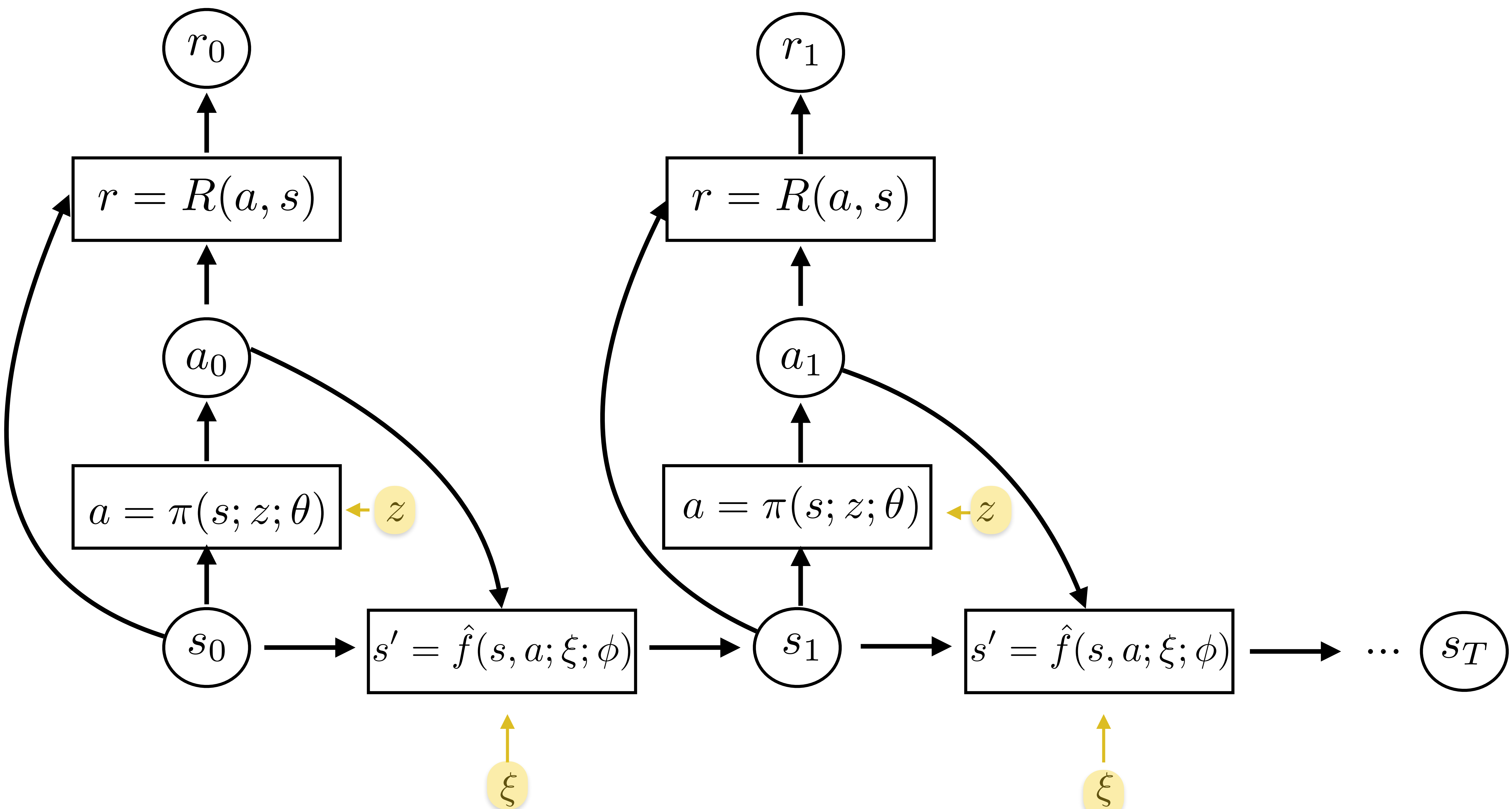


$$a = \mu(s;\theta) + z\sigma(s;\theta)$$

(where are the other versions? We will see them in the model based RL lecture)

End-to-end model based RL

Re-parametrization trick for both policies and dynamics



N. Heess, G. Wayne, D. Silver, et al. "Learning continuous control policies by stochastic value gradients". In: *NIPS*. 2015

Deep Deterministic Policy Gradients

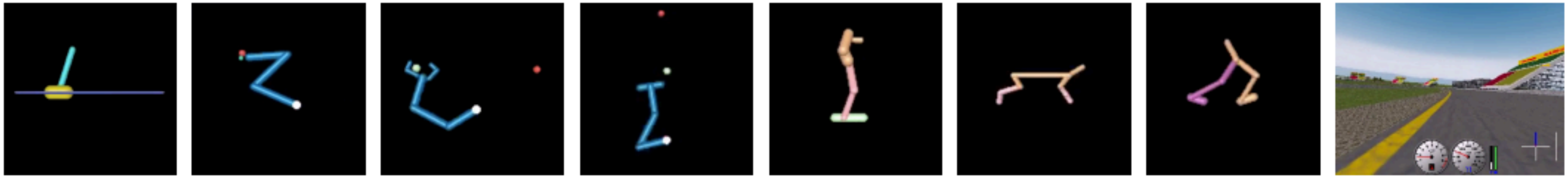


Figure 1: Example screenshots of a sample of environments we attempt to solve with DDPG. In order from the left: the cartpole swing-up task, a reaching task, a gasp and move task, a puck-hitting task, a monoped balancing task, two locomotion tasks and Torcs (driving simulator). We tackle all tasks using both low-dimensional feature vector and high-dimensional pixel inputs. Detailed descriptions of the environments are provided in the supplementary. Movies of some of the learned policies are available at `https://goo.gl/J4PIAz`.

https://www.youtube.com/watch?v=tJBIqkC1wWM&feature=youtu.be

Deep Deterministic Policy Gradients

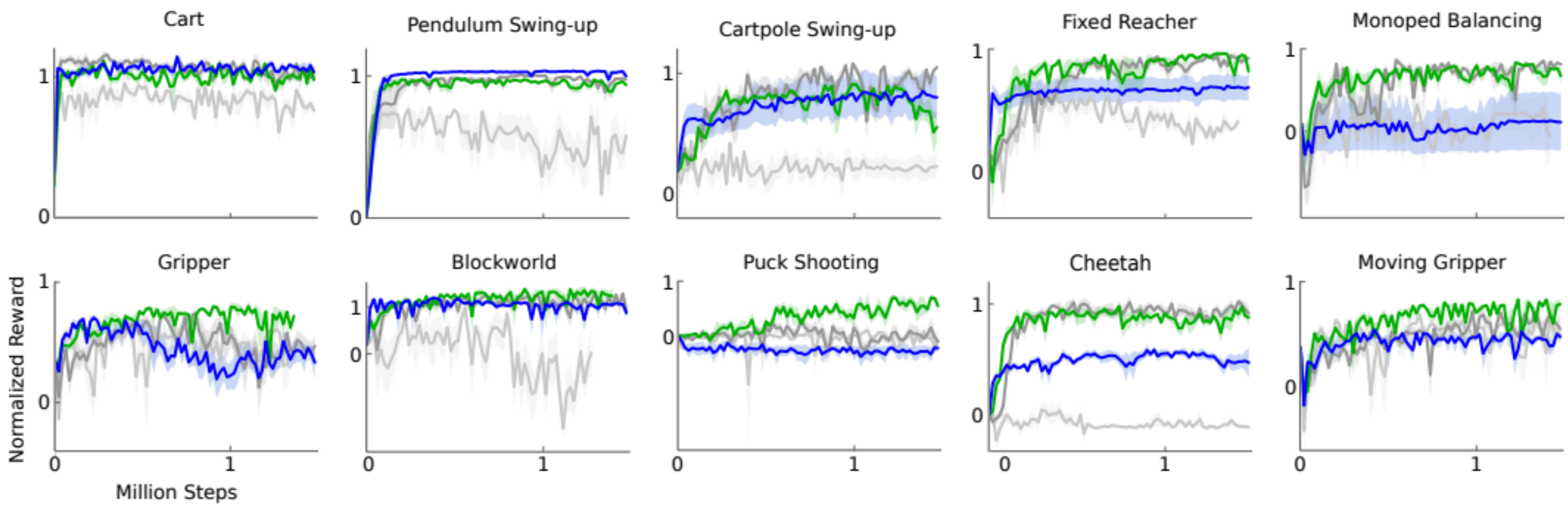


Figure 2: Performance curves for a selection of domains using variants of DPG: original DPG algorithm (minibatch NFQCA) with batch normalization (light grey), with target network (dark grey), with target networks and batch normalization (green), with target networks from pixel-only inputs (blue). Target networks are crucial.

State representation input can be pixels or robotic configuration and target locations

https://www.youtube.com/watch?v=tJBIqkC1wWM&feature=youtu.be

Model Free Methods - Comparison

Task	Random	REINFORCE	TNPG	RWR	REPS	TRPO	CEM	CMA-ES	DDPG
Cart-Pole Balancing	77.1 ± 0.0	4693.7 ± 14.0	**3986.4 ± 748.9**	**4861.5 ± 12.3**	565.6 ± 137.6	**4869.8 ± 37.6**	4815.4 ± 4.8	2440.4 ± 568.3	4634.4 ± 87.8
Inverted Pendulum*	−153.4 ± 0.2	13.4 ± 18.0	**209.7 ± 55.5**	84.7 ± 13.8	−113.3 ± 4.6	**247.2 ± 76.1**	38.2 ± 25.7	−40.1 ± 5.7	40.0 ± 244.6
Mountain Car	−415.4 ± 0.0	−67.1 ± 1.0	**-66.5 ± 4.5**	−79.4 ± 1.1	−275.6 ± 166.3	**-61.7 ± 0.9**	−66.0 ± 2.4	−85.0 ± 7.7	−288.4 ± 170.3
Acrobot	−1904.5 ± 1.0	−508.1 ± 91.0	−395.8 ± 121.2	−352.7 ± 35.9	−1001.5 ± 10.8	−326.0 ± 24.4	−436.8 ± 14.7	−785.6 ± 13.1	**-223.6 ± 5.8**
Double Inverted Pendulum*	149.7 ± 0.1	4116.5 ± 65.2	**4455.4 ± 37.6**	3614.8 ± 368.1	446.7 ± 114.8	**4412.4 ± 50.4**	2566.2 ± 178.9	1576.1 ± 51.3	2863.4 ± 154.0
Swimmer*	−1.7 ± 0.1	92.3 ± 0.1	**96.0 ± 0.2**	60.7 ± 5.5	3.8 ± 3.3	**96.0 ± 0.2**	68.8 ± 2.4	64.9 ± 1.4	85.8 ± 1.8
Hopper	8.4 ± 0.0	714.0 ± 29.3	**1155.1 ± 57.9**	553.2 ± 71.0	86.7 ± 17.6	**1183.3 ± 150.0**	63.1 ± 7.8	20.3 ± 14.3	267.1 ± 43.5
2D Walker	−1.7 ± 0.0	506.5 ± 78.8	**1382.6 ± 108.2**	136.0 ± 15.9	−37.0 ± 38.1	**1353.8 ± 85.0**	84.5 ± 19.2	77.1 ± 24.3	318.4 ± 181.6
Half-Cheetah	−90.8 ± 0.3	1183.1 ± 69.2	**1729.5 ± 184.6**	376.1 ± 28.2	34.5 ± 38.0	**1914.0 ± 120.1**	330.4 ± 274.8	441.3 ± 107.6	**2148.6 ± 702.7**
Ant*	13.4 ± 0.7	548.3 ± 55.5	**706.0 ± 127.7**	37.6 ± 3.1	39.0 ± 9.8	**730.2 ± 61.3**	49.2 ± 5.9	17.8 ± 15.5	326.2 ± 20.8
Simple Humanoid	41.5 ± 0.2	128.1 ± 34.0	**255.0 ± 24.5**	93.3 ± 17.4	28.3 ± 4.7	**269.7 ± 40.3**	60.6 ± 12.9	28.7 ± 3.9	99.4 ± 28.1
Full Humanoid	13.2 ± 0.1	262.2 ± 10.5	**288.4 ± 25.2**	46.7 ± 5.6	41.7 ± 6.1	**287.0 ± 23.4**	36.9 ± 2.9	N/A ± N/A	119.0 ± 31.2
Cart-Pole Balancing (LS)*	77.1 ± 0.0	420.9 ± 265.5	**945.1 ± 27.8**	68.9 ± 1.5	898.1 ± 22.1	**960.2 ± 46.0**	227.0 ± 223.0	68.0 ± 1.6	
Inverted Pendulum (LS)	−122.1 ± 0.1	−13.4 ± 3.2	**0.7 ± 6.1**	−107.4 ± 0.2	−87.2 ± 8.0	**4.5 ± 4.1**	−81.2 ± 33.2	−62.4 ± 3.4	
Mountain Car (LS)	−83.0 ± 0.0	−81.2 ± 0.6	**-65.7** ± 9.0	−81.7 ± 0.1	−82.6 ± 0.4	**-64.2 ± 9.5**	**-68.9 ± 1.3**	**-73.2 ± 0.6**	
Acrobot (LS)*	−393.2 ± 0.0	−128.9 ± 11.6	**-84.6 ± 2.9**	−235.9 ± 5.3	−379.5 ± 1.4	**-83.3 ± 9.9**	−149.5 ± 15.3	−159.9 ± 7.5	
Cart-Pole Balancing (NO)*	101.4 ± 0.1	616.0 ± 210.8	**916.3 ± 23.0**	93.8 ± 1.2	99.6 ± 7.2	606.2 ± 122.2	181.4 ± 32.1	104.4 ± 16.0	
Inverted Pendulum (NO)	−122.2 ± 0.1	6.5 ± 1.1	**11.5 ± 0.5**	−110.0 ± 1.4	−119.3 ± 4.2	**10.4 ± 2.2**	−55.6 ± 16.7	−80.3 ± 2.8	
Mountain Car (NO)	−83.0 ± 0.0	−74.7 ± 7.8	**-64.5 ± 8.6**	−81.7 ± 0.1	−82.9 ± 0.1	**-60.2 ± 2.0**	−67.4 ± 1.4	−73.5 ± 0.5	
Acrobot (NO)*	−393.5 ± 0.0	**-186.7 ± 31.3**	**-164.5 ± 13.4**	−233.1 ± 0.4	−258.5 ± 14.0	**-149.6 ± 8.6**	−213.4 ± 6.3	−236.6 ± 6.2	
Cart-Pole Balancing (SI)*	76.3 ± 0.1	431.7 ± 274.1	**980.5 ± 7.3**	69.0 ± 2.8	702.4 ± 196.4	**980.3 ± 5.1**	746.6 ± 93.2	71.6 ± 2.9	
Inverted Pendulum (SI)	−121.8 ± 0.2	−5.3 ± 5.6	**14.8 ± 1.7**	−108.7 ± 4.7	−92.8 ± 23.9	**14.1 ± 0.9**	−51.8 ± 10.6	−63.1 ± 4.8	
Mountain Car (SI)	−82.7 ± 0.0	−63.9 ± 0.2	**-61.8 ± 0.4**	−81.4 ± 0.1	−80.7 ± 2.3	**-61.6 ± 0.4**	−63.9 ± 1.0	−66.9 ± 0.6	
Acrobot (SI)*	−387.8 ± 1.0	**-169.1 ± 32.3**	**-156.6 ± 38.9**	−233.2 ± 2.6	−216.1 ± 7.7	**-170.9 ± 40.3**	−250.2 ± 13.7	−245.0 ± 5.5	
Swimmer + Gathering	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
Ant + Gathering	−5.8 ± 5.0	−0.1 ± 0.1	−0.4 ± 0.1	−5.5 ± 0.5	−6.7 ± 0.7	−0.4 ± 0.0	−4.7 ± 0.7	N/A ± N/A	−0.3 ± 0.3
Swimmer + Maze	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
Ant + Maze	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	N/A ± N/A	0.0 ± 0.0

Y. Duan, X. Chen, R. Houthooft, et al. "Benchmarking Deep Reinforcement Learning for Continuous Control"

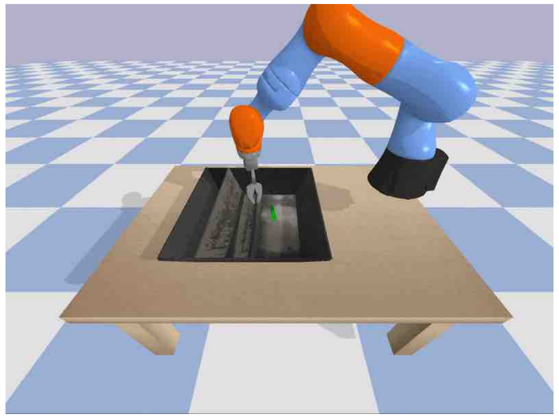
Carnegie Mellon
School of Computer Science

Deep Reinforcement Learning and Control

Multigoal RL

Katerina Fragkiadaki

So far we train one policy/value function per task, e.g., win the game of Tetris, win the game of Go, reach to a *particular* location, put the green cube inside the gray bucket, etc.



Universal value function Approximators

$$V(s;\theta) \rightarrow V(s,g;\theta)$$

$$\pi(s;\theta) \rightarrow \pi(s,g;\theta)$$

All the methods we have learnt so far can be used.

At the beginning of an episode, **we sample not only a start state but also a goal g**, which stays constant throughout the episode

The experience tuples should contain the goal.

$$(s,a,r,s') \rightarrow \left(s,g,a,r,s'\right)$$

Universal Value Function Approximators, Schaul et al.

Universal value function Approximators

$$V(s,\theta) \quad \rightarrow \quad V(s,\theta,g)$$

$$\pi(s;\theta) \quad \rightarrow \quad \pi(s,g;\theta)$$

What should be my goal representation?

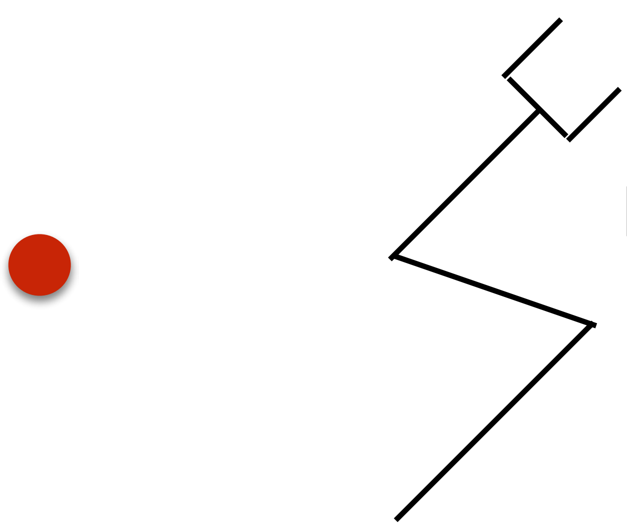
(not an easy question)

- **Manual**: 3d centroids of objects, robot joint angles and velocities, 3d location of the gripper, etc.
- **Learnt**: We supply **a target image as the goal**, and the method learns to map it to an embedding vector, e.g., asymmetric actor-critic, Lerrel et al.

Hindsight Experience Replay

Marcin Andrychowicz*, Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, Pieter Abbeel†, Wojciech Zaremba†
OpenAI

Main idea: use failed executions under one goal g, as successful executions under an alternative goal g' (which is where we ended spat the end of the episode)



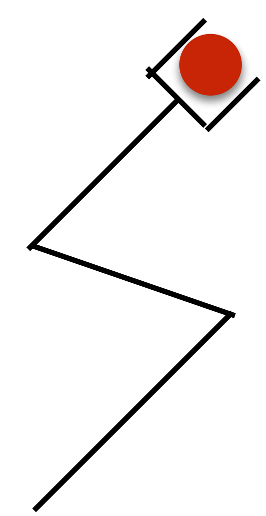
No reward :-(

Goal g

Our reacher at the end of the episode

$(s, g, a, 0, s')$

Goal g'



reward :-)

Our reacher at the end of the episode
$(s, g', a, 1, s')$

Hindsight Experience Replay

Marcin Andrychowicz*, **Filip Wolski**, **Alex Ray**, **Jonas Schneider**, **Rachel Fong**,
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OpenAI

Main idea: use failed executions under one goal g, as successful executions under an alternative goal g’ (which is where we ended spat the end of the episode)

Hindsight Experience Replay

Algorithm 1 Hindsight Experience Replay (HER)

Given:

- an off-policy RL algorithm $\mathbb{A}$, ▷ e.g. DQN, DDPG, NAF, SDQN
- a strategy $\mathbb{S}$ for sampling goals for replay, ▷ e.g. $\mathbb{S}(s_0, \ldots, s_T) = m(s_T)$
- a reward function $r : \mathcal{S} \times \mathcal{A} \times \mathcal{G} \to \mathbb{R}$. ▷ e.g. $r(s, a, g) = -[f_g(s) = 0]$

Initialize $\mathbb{A}$ ▷ e.g. initialize neural networks
Initialize replay buffer R
for episode $= 1, M$ **do**
  Sample a goal g and an initial state s_0.
  for $t = 0, T-1$ **do**
    Sample an action a_t using the behavioral policy from $\mathbb{A}$:
      $a_t \leftarrow \pi_b(s_t||g)$ ▷ || denotes concatenation
    Execute the action a_t and observe a new state s_{t+1}
  end for
  for $t = 0, T-1$ **do**
    $r_t := r(s_t, a_t, g)$
    Store the transition $(s_t||g, a_t, r_t, s_{t+1}||g)$ in R ▷ standard experience replay
    Sample a set of additional goals for replay $G := \mathbb{S}($**current episode**$)$
    for $g' \in G$ **do**
      $r' := r(s_t, a_t, g')$
      Store the transition $(s_t||g', a_t, r', s_{t+1}||g')$ in R ▷ HER
    end for
  end for
  for $t = 1, N$ **do**
    Sample a minibatch B from the replay buffer R
    Perform one step of optimization using $\mathbb{A}$ and minibatch B
  end for
end for

Usually as additional goal we pick the goal that this episode achieved, and the reward becomes non zero

Hindsight Experience Replay

Reward shaping: instead of using binary rewards, use continuous rewards, e.g., by considering Euclidean distances from goal configuration

HER does not require reward shaping! :-)

The burden goes from designing the reward to designing the goal encoding.. :-(

Hindsight Experience Replay