IASD M2 at Paris Dauphine

Deep Reinforcement Learning

22: Transfer and Multi-Task Learning

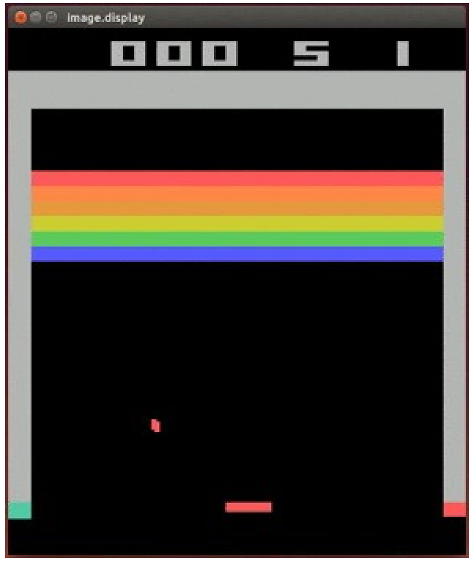
Eric Benhamou David Saltiel

Acknowledgement

These materials are based on the seminal course of Sergey Levine CS285

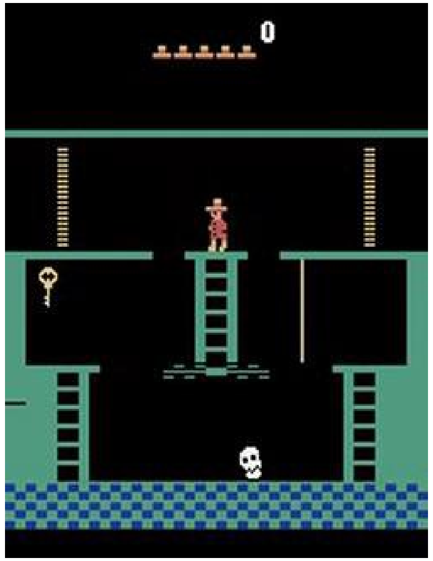
What’s the problem?

this is easy (mostly)

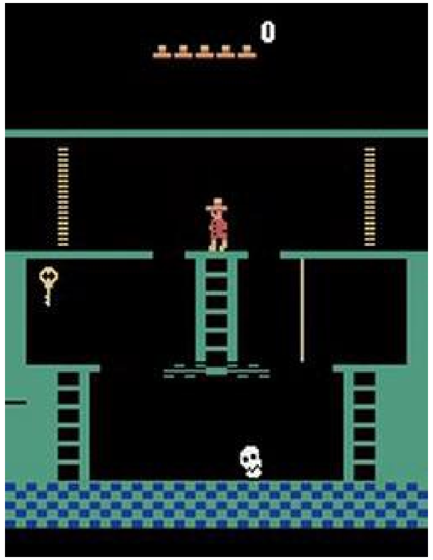


Why?

this is impossible

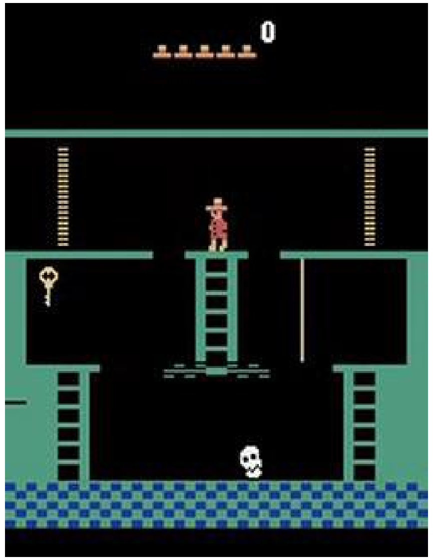


Montezuma’s revenge



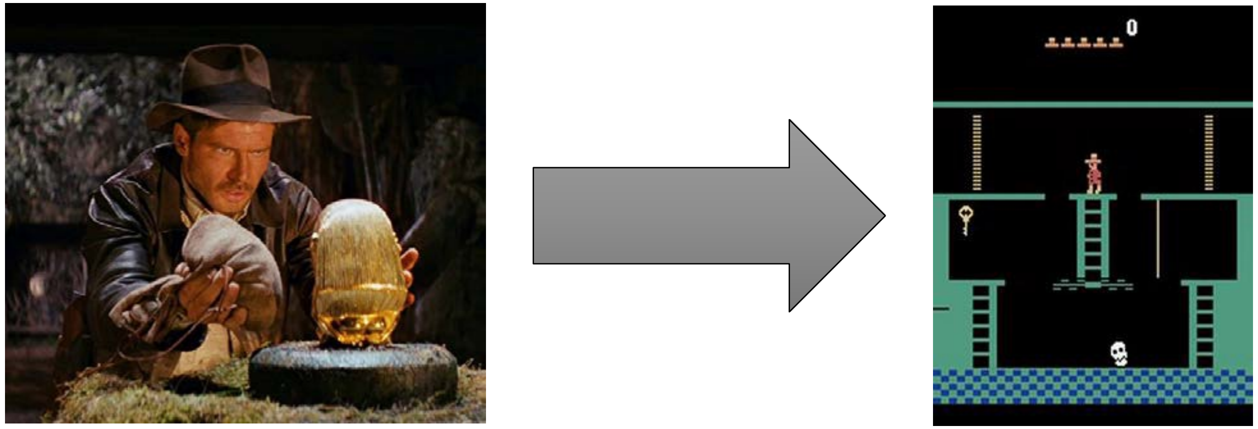
- Getting key = reward
- Opening door = reward
- Getting killed by skull = bad

Montezuma’s revenge



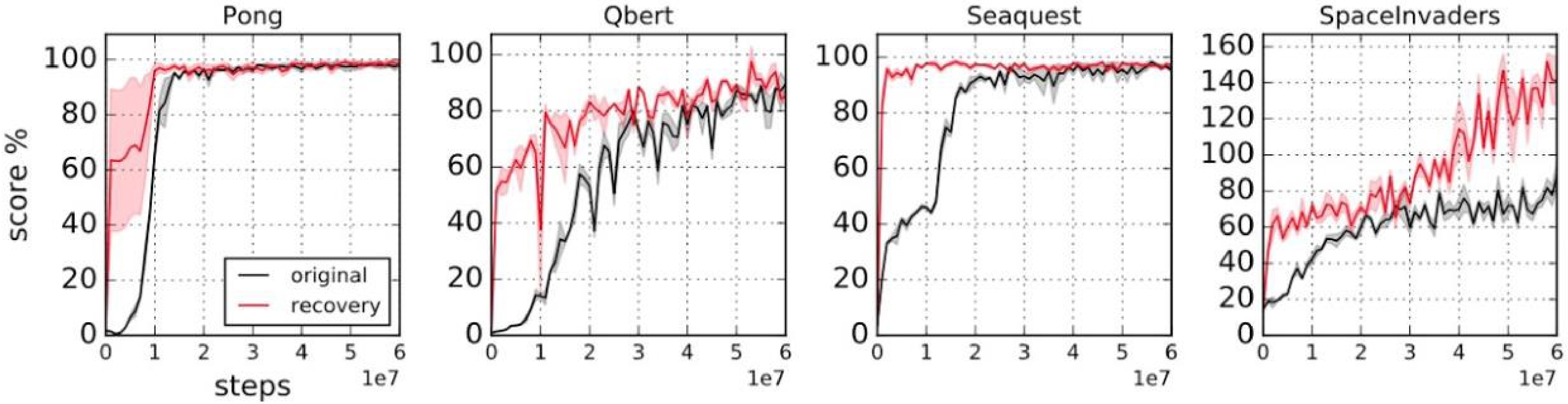
- We know what to do because we **understand** what these sprites mean!
- Key: we know it opens doors!
- Ladders: we know we can climb them!
- Skull: we don’t know what it does, but we know it can’t be good!
- **Prior understanding of problem structure can help us solve complex tasks quickly!**

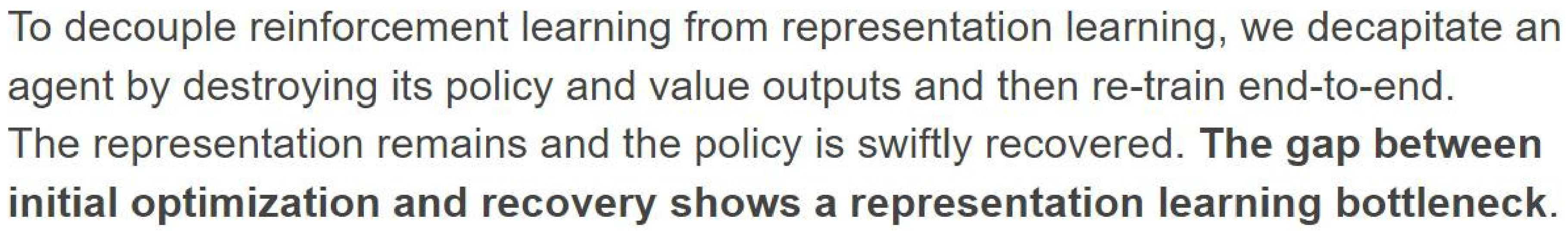
Can RL use the same prior knowledge as us?



- If we’ve solved prior tasks, we might acquire useful knowledge for solving a new task
- How is the knowledge stored?
    - Q-function: tells us which actions or states are good
    - Policy: tells us which actions are potentially useful
        - some actions are never useful!
    - Models: what are the laws of physics that govern the world?
    - Features/hidden states: provide us with a good representation
        - Don’t underestimate this!

Aside: the representation bottleneck




To decouple reinforcement learning from representation learning, we decapitate an agent by destroying its policy and value outputs and then re-train end-to-end. The representation remains and the policy is swiftly recovered. **The gap between initial optimization and recovery shows a representation learning bottleneck**.

slide adapted from E. Schelhamer, “Loss is its own reward”

Transfer learning terminology

transfer learning: using experience from one set of tasks for faster learning and better performance on a new task

in RL, task = MDP!

source domain

target domain

"shot": number of attempts in the target domain

1shot: just run a policy trained in the source domain

2 shot: try the task once

few shot: try the task a few times

How can we frame transfer learning problems?

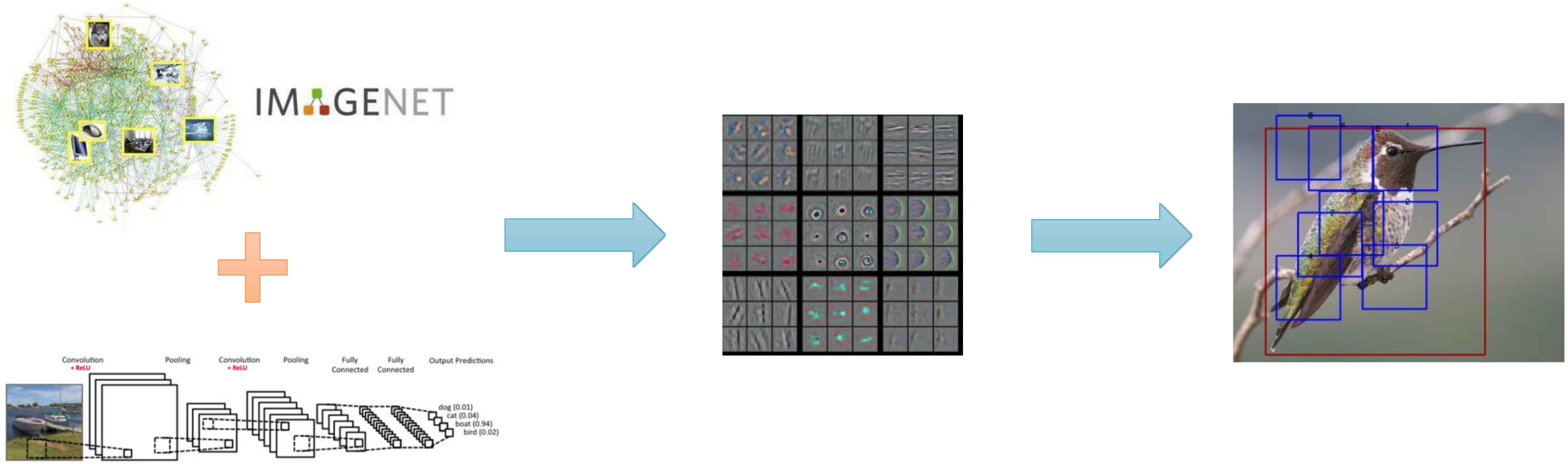
No single solution! Survey of various recent research papers

1. Forward transfer: train on one task, transfer to a new task
   a) Transferring visual representations & domain adaptation
   b) Domain adaptation in reinforcement learning
   c) Randomization
2. Multi-task transfer: train on many tasks, transfer to a new task
   a) Sharing representations and layers across tasks in multi-task learning
   b) Contextual policies
   c) Optimization challenges for multi-task learning
   d) Algorithms
3. Transferring models and value functions
   a) Model-based RL as a mechanism for transfer
   b) Successor features & representations

Forward Transfer

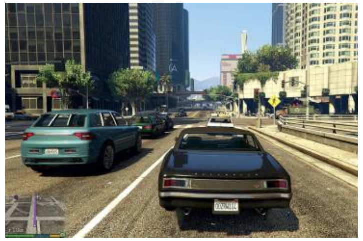
Pretraining + Finetuning

The most popular transfer learning method in (supervised) deep learning!

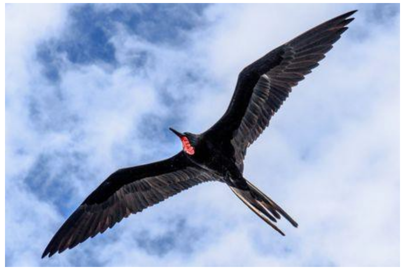


What issues are we likely to face?

➢**Domain shift:** representations learned in the source domain might not work well in the target domain

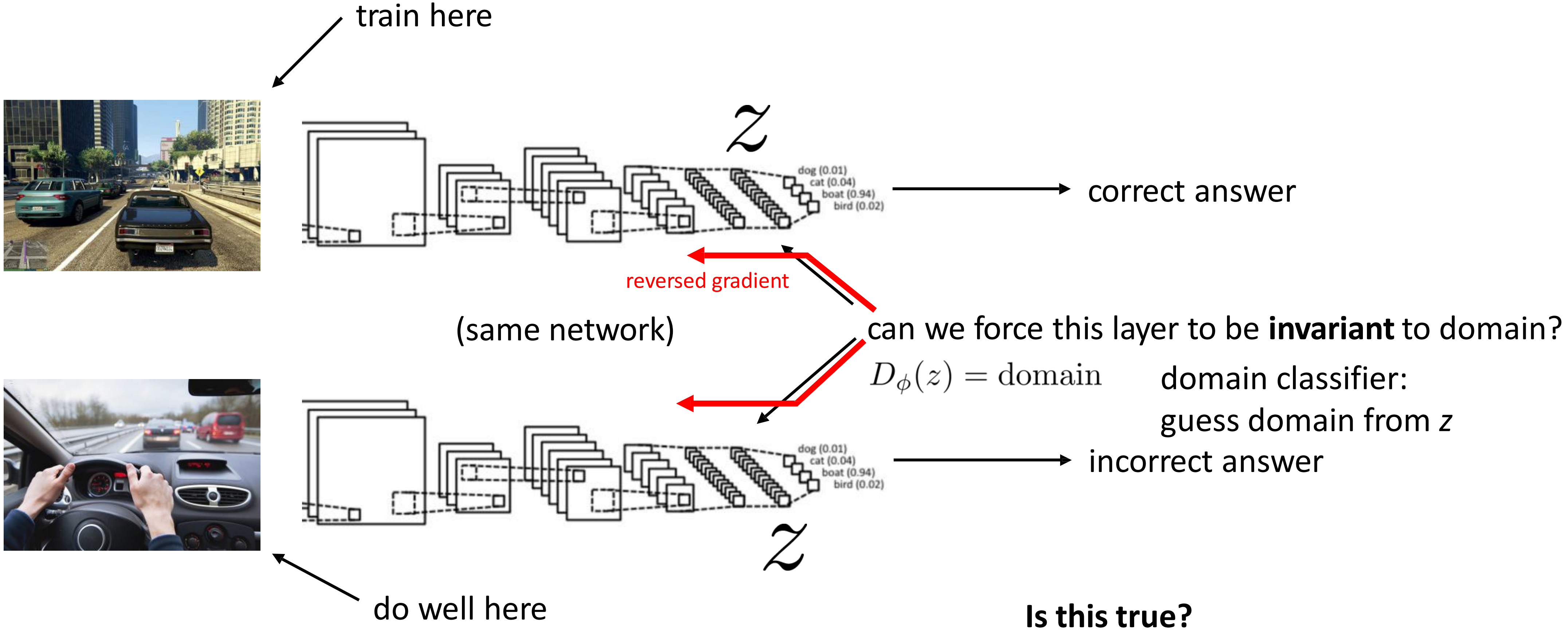


➢**Difference in the MDP:** some things that are possible to do in the source domain are not possible to do in the target domain



➢**Finetuning issues:** if pretraining & finetuning, the finetuning process may still need to explore, but optimal policy during finetuning may be deterministic!

Domain adaptation in computer vision



train here

z

correct answer

reversed gradient

(same network)

can we force this layer to be **invariant** to domain?

$D_\phi(z) = \text{domain}$

domain classifier: guess domain from *z*

incorrect answer

z

do well here

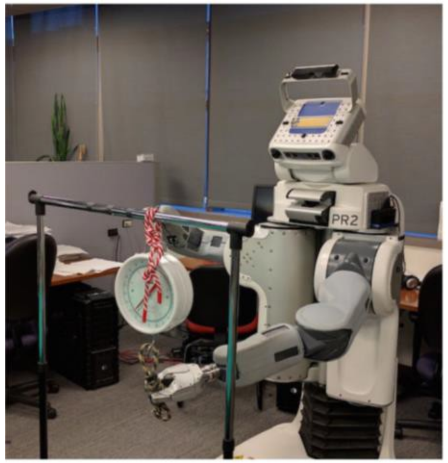
Is this true?

Invariance assumption: everything that is **different** between domains is **irrelevant**

formally:

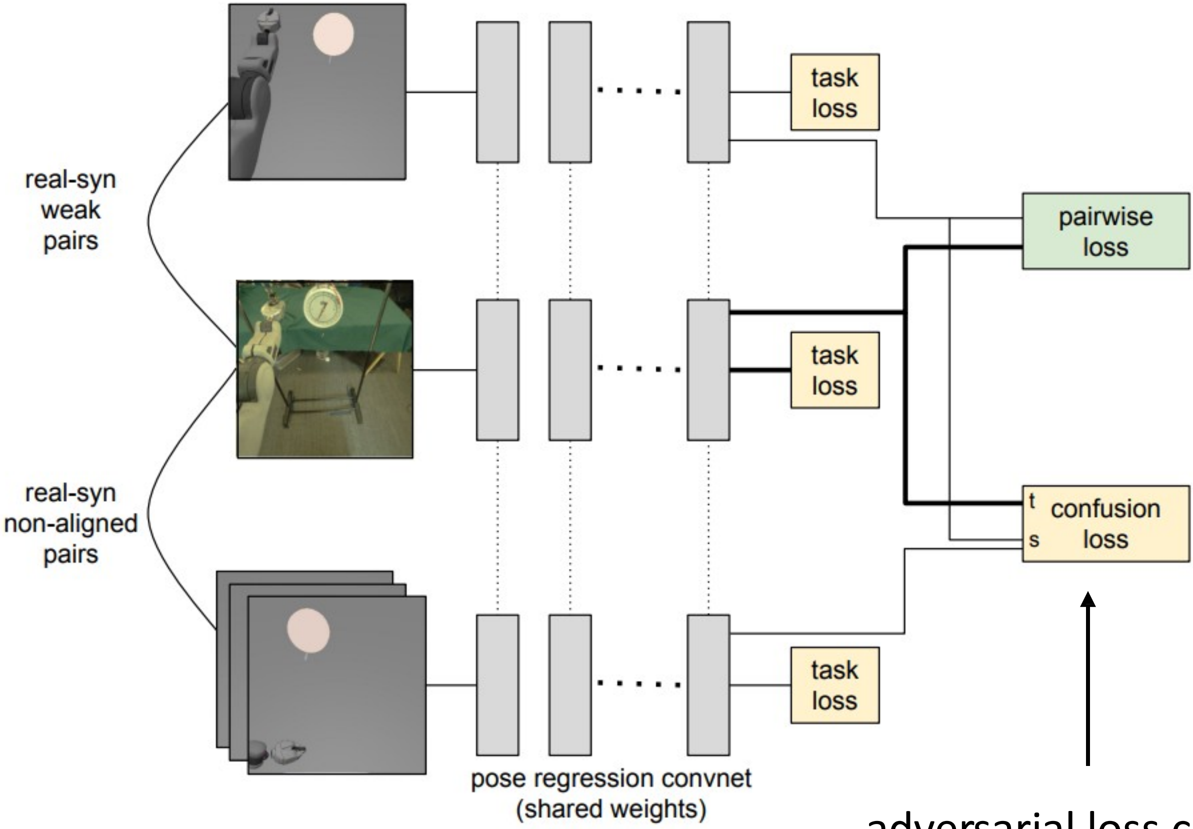
$p(x)$ is different   exists some $z = f(x)$ such that $p(y|z) = p(y|x)$, but $p(z)$ is same

How do we apply this idea in RL?



simulated images

real images

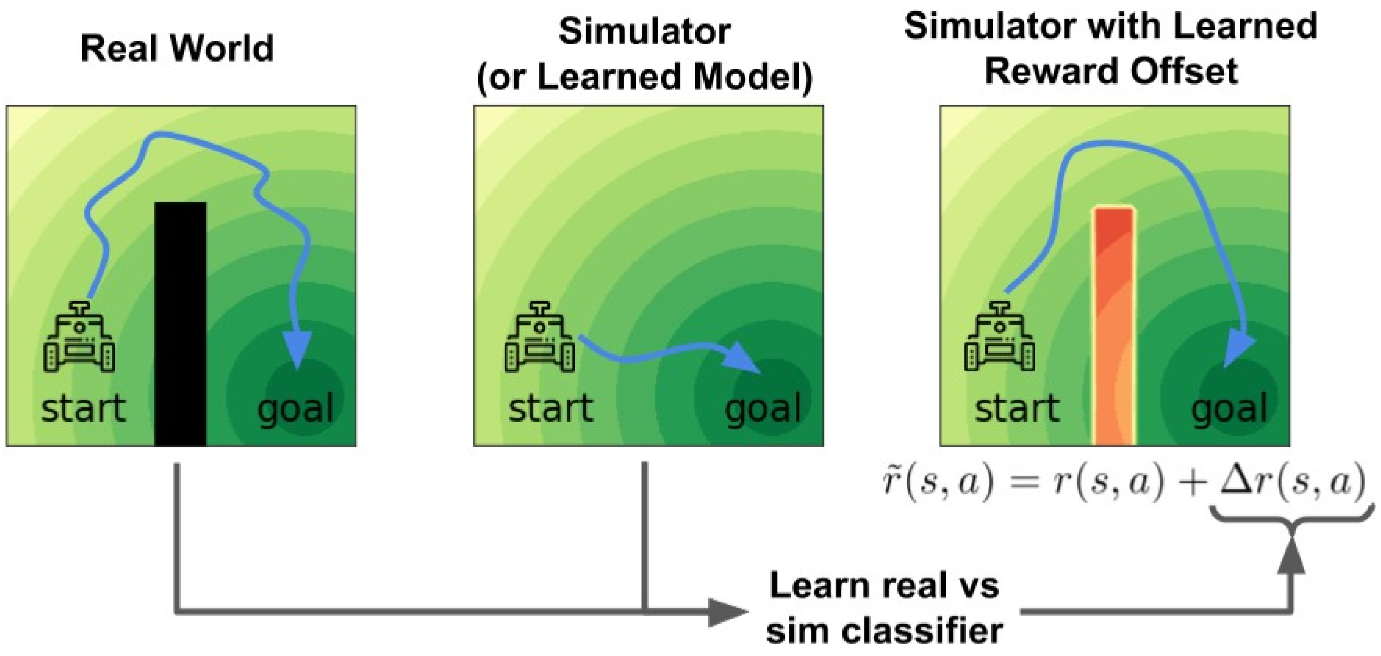


adversarial loss causes internal CNN features to be indistinguishable for sim and real

Tzeng*, Devin*, et al., "Adapting Visuomotor Representations with Weak Pairwise Constraints"

Domain adaptation in RL for dynamics?

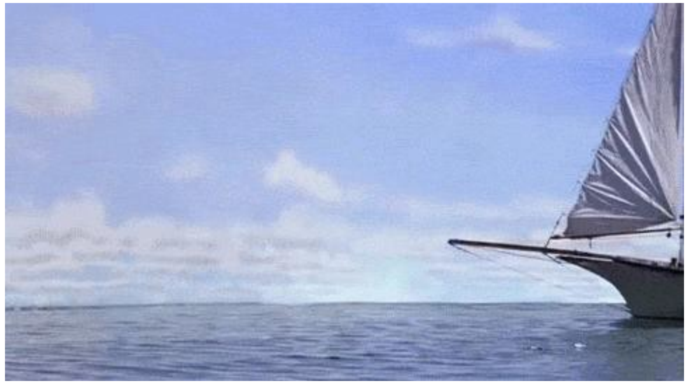
Why is **invariance** not enough when the dynamics don't match?


Real World
Simulator (or Learned Model)
Simulator with Learned Reward Offset
start
goal
start
goal
start
goal
Learn real vs sim classifier

$$\tilde{r}(s,a) = r(s,a) + \underbrace{\Delta r(s,a)}$$

$$\Delta r(s_t, a_t, s_{t+1}) = \log p_{\text{target}}(s_{t+1} \mid s_t, a_t) - \log p_{\text{source}}(s_{t+1} \mid s_t, a_t).$$

$$\Delta r(s_t, a_t, s_{t+1}) = \log p(\text{target} \mid s_t, a_t, s_{t+1}) - \log p(\text{target} \mid s_t, a_t) - \log p(\text{source} \mid s_t, a_t, s_{t+1}) + \log p(\text{source} \mid s_t, a_t)$$

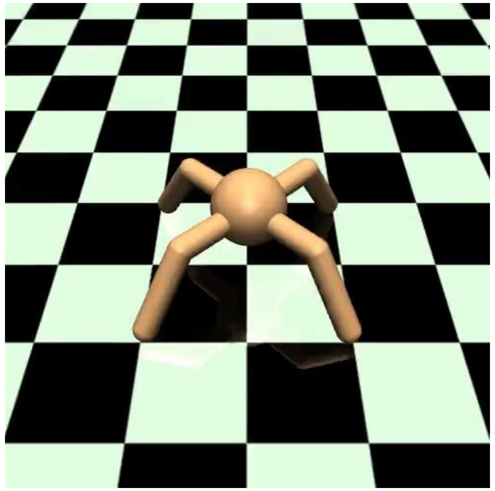


When might this **not** work?

Eysenbach et al., "Off-Dynamics Reinforcement Learning: Training for Transfer with Domain Classifiers"

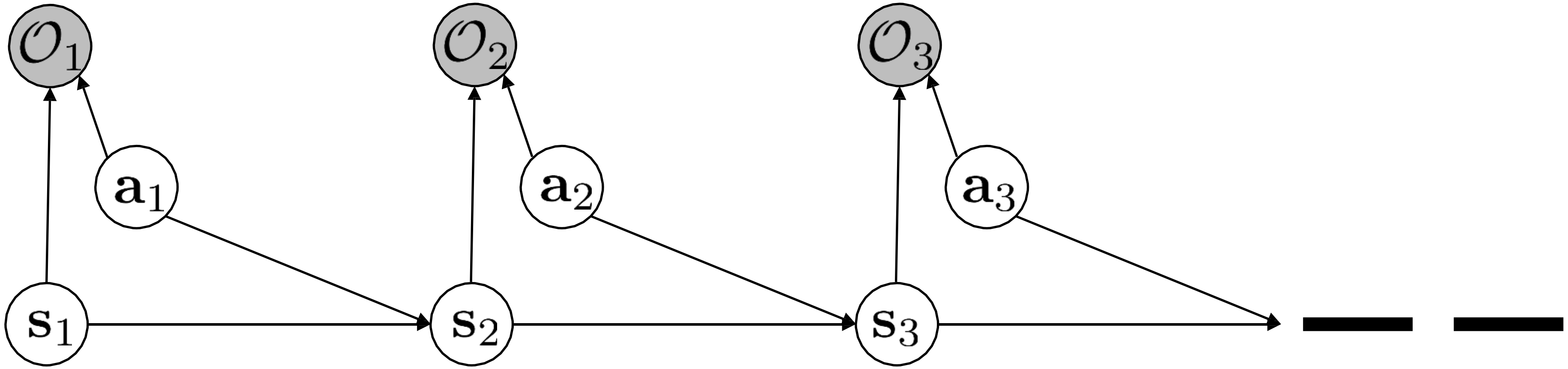
What if we can also finetune?

1. RL tasks are generally much less diverse
   - Features are less general
   - Policies & value functions become overly specialized
2. Optimal policies in fully observed MDPs are deterministic
   - Loss of exploration at convergence
   - Low-entropy policies adapt very slowly to new settings



Finetuning with maximum-entropy policies

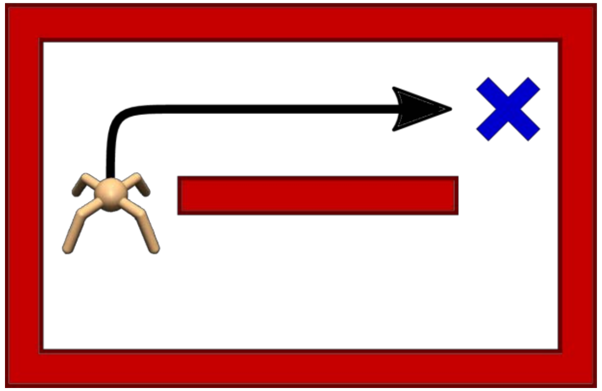
How can we increase diversity and entropy?

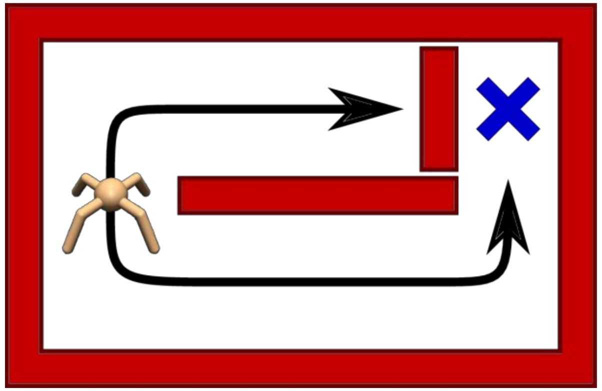


$$\pi(\mathbf{a}|\mathbf{s}) = \exp(Q_\phi(\mathbf{s},\mathbf{a}) - V(\mathbf{s})) \text{ optimizes } \sum_t E_{\pi(\mathbf{s}_t,\mathbf{a}_t)}[r(\mathbf{s}_t,\mathbf{a}_t)] + E_{\pi(\mathbf{s}_t)}\underbrace{[\mathcal{H}(\pi(\mathbf{a}_t|\mathbf{s}_t))]}_{\text{policy entropy}}$$

Act **as randomly as possible** while collecting high rewards!

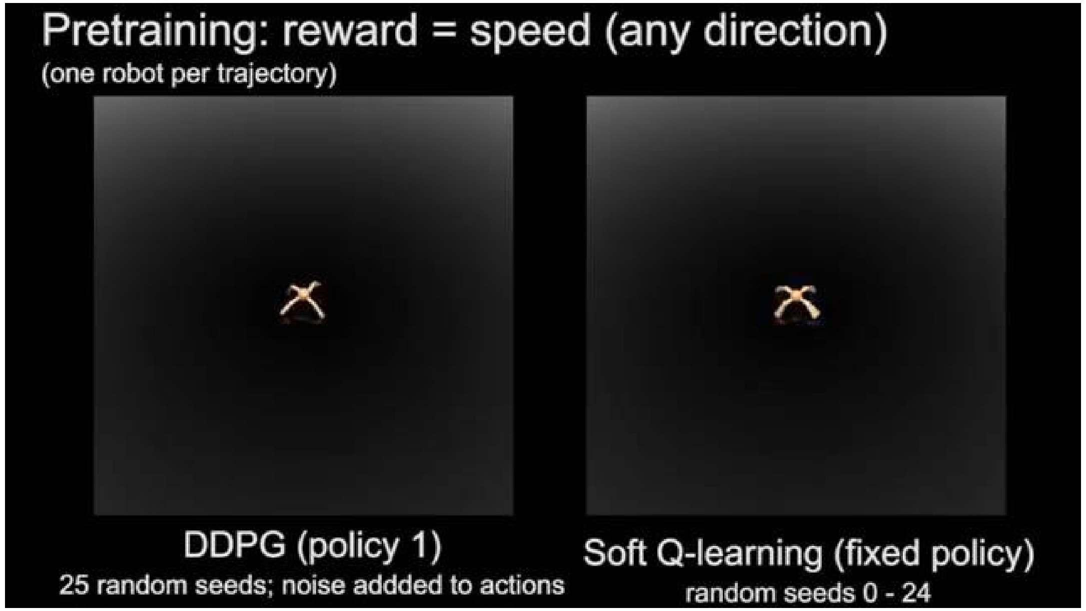
Example: pre-training for robustness

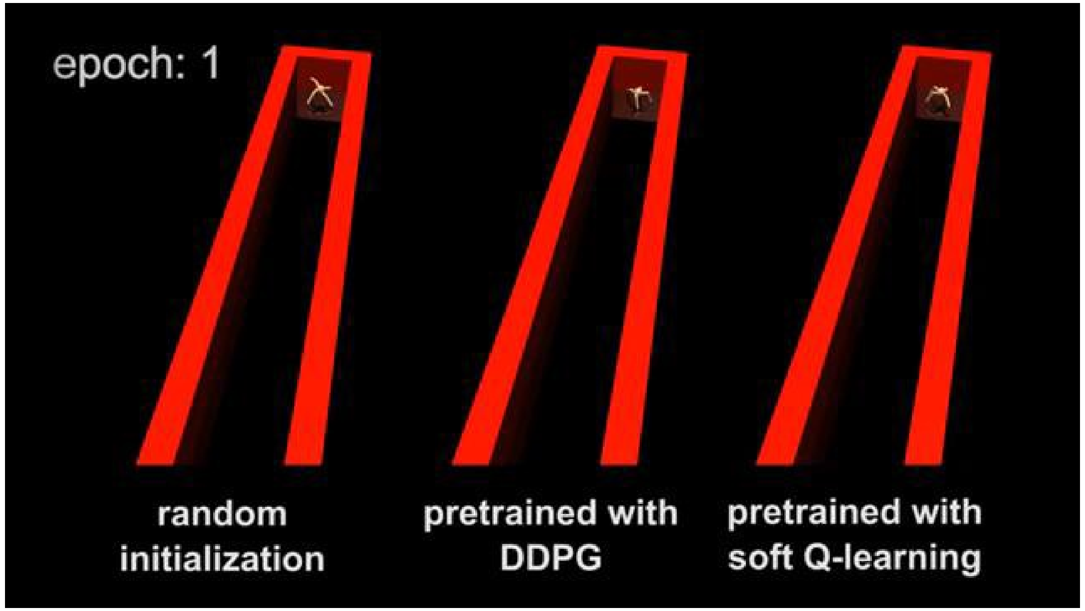


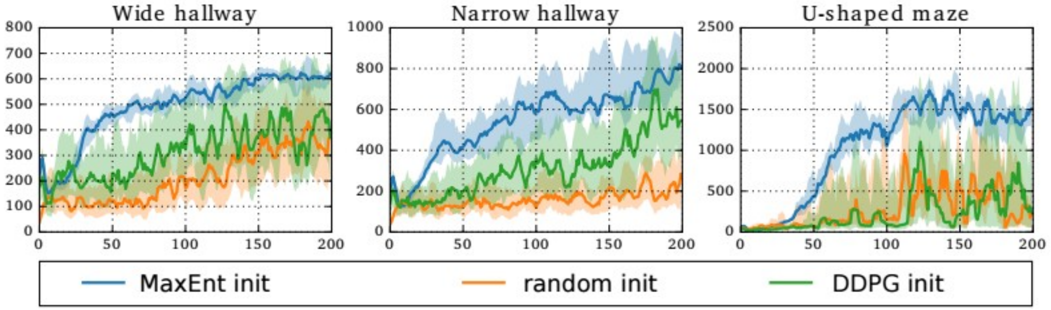


Learning to solve a task **in all possible ways** provides for more robust transfer!

Example: pre-training for diversity


Pretraining: reward = speed (any direction)
(one robot per trajectory)
DDPG (policy 1)
25 random seeds; noise addded to actions
Soft Q-learning (fixed policy)
random seeds 0 - 24





Haarnoja*, Tang*, et al. "Reinforcement Learning with Deep Energy-Based Policies"

Domain adaptation: suggested readings

Tzeng, Hoffman, Zhang, Saenko, Darrell. **Deep Domain Confusion: Maximizing for Domain Invariance**. 2014.

Ganin, Ustinova, Ajakan, Germain, Larochelle, Laviolette, Marchand, Lempitsky. **Domain-Adversarial Training of Neural Networks**. 2015.

Tzeng*, Devin*, et al., **Adapting Visuomotor Representations with Weak Pairwise Constraints**. 2016.

Eysenbach et al., **Off-Dynamics Reinforcement Learning: Training for Transfer with Domain Classifiers**. 2020.

…and many many others!

Finetuning: suggested readings

Finetuning via MaxEnt RL: Haarnoja*, Tang*, et al. (2017). **Reinforcement Learning with Deep Energy-Based Policies.**

Andreas et al. **Modular multitask reinforcement learning with policy sketches.** 2017.

Florensa et al. **Stochastic neural networks for hierarchical reinforcement learning.** 2017.

Kumar et al. **One Solution is Not All You Need: Few-Shot Extrapolation via Structured MaxEnt RL.** 2020

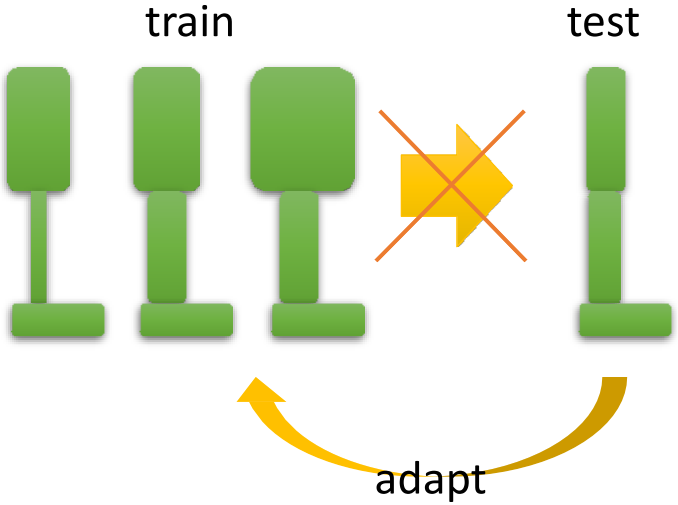
…and many many others!

Forward Transfer with Randomization

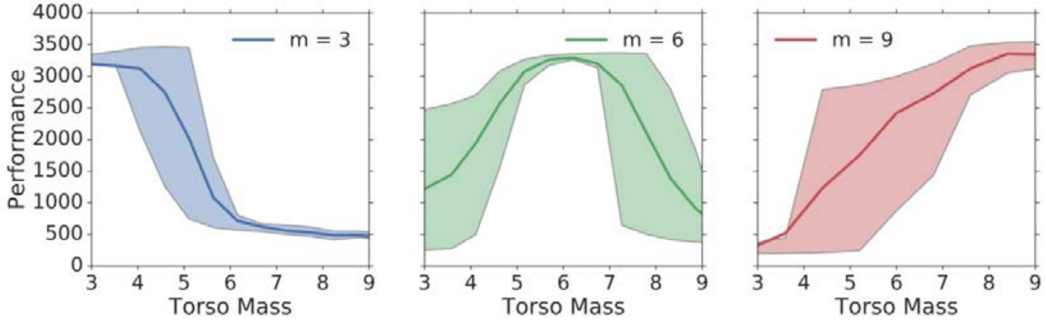
What if we can manipulate the source domain?

- So far: source domain (e.g., empty room) and target domain (e.g., corridor) are fixed
- What if we can **design** the source domain, and we have a **difficult** target domain?
  - Often the case for simulation to real world transfer

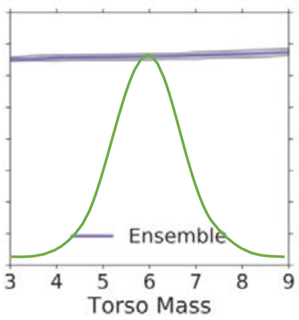
EPOpt: randomizing physical parameters



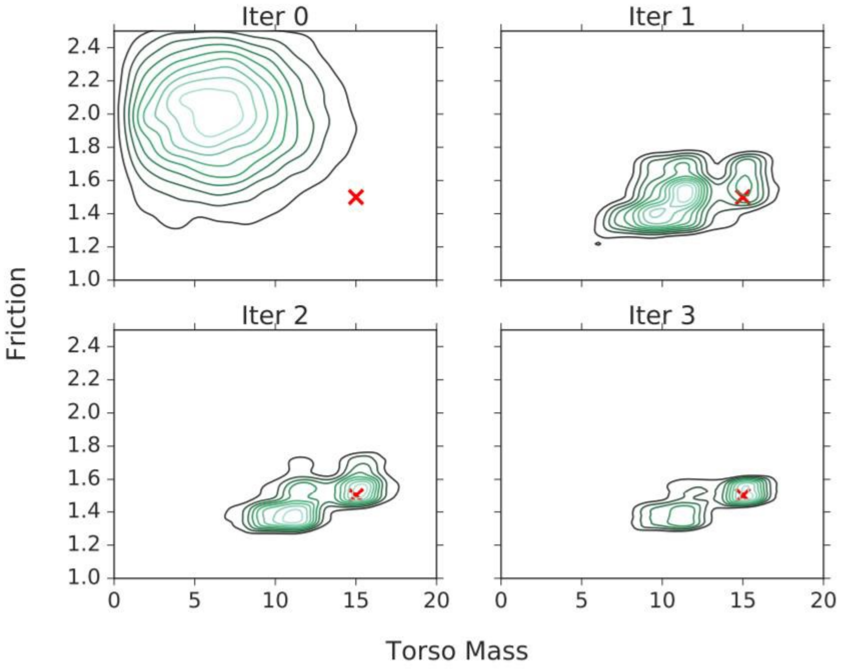
training on single torso mass



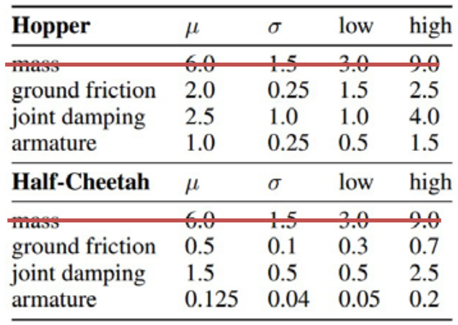
training on model ensemble



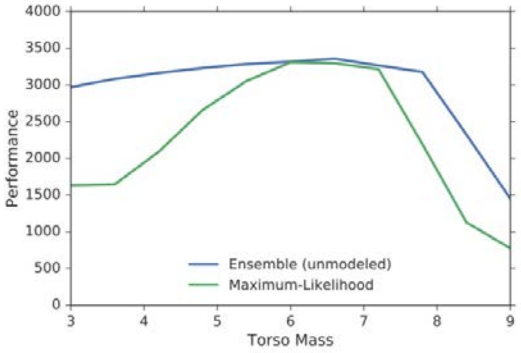
ensemble adaptation



unmodeled effects

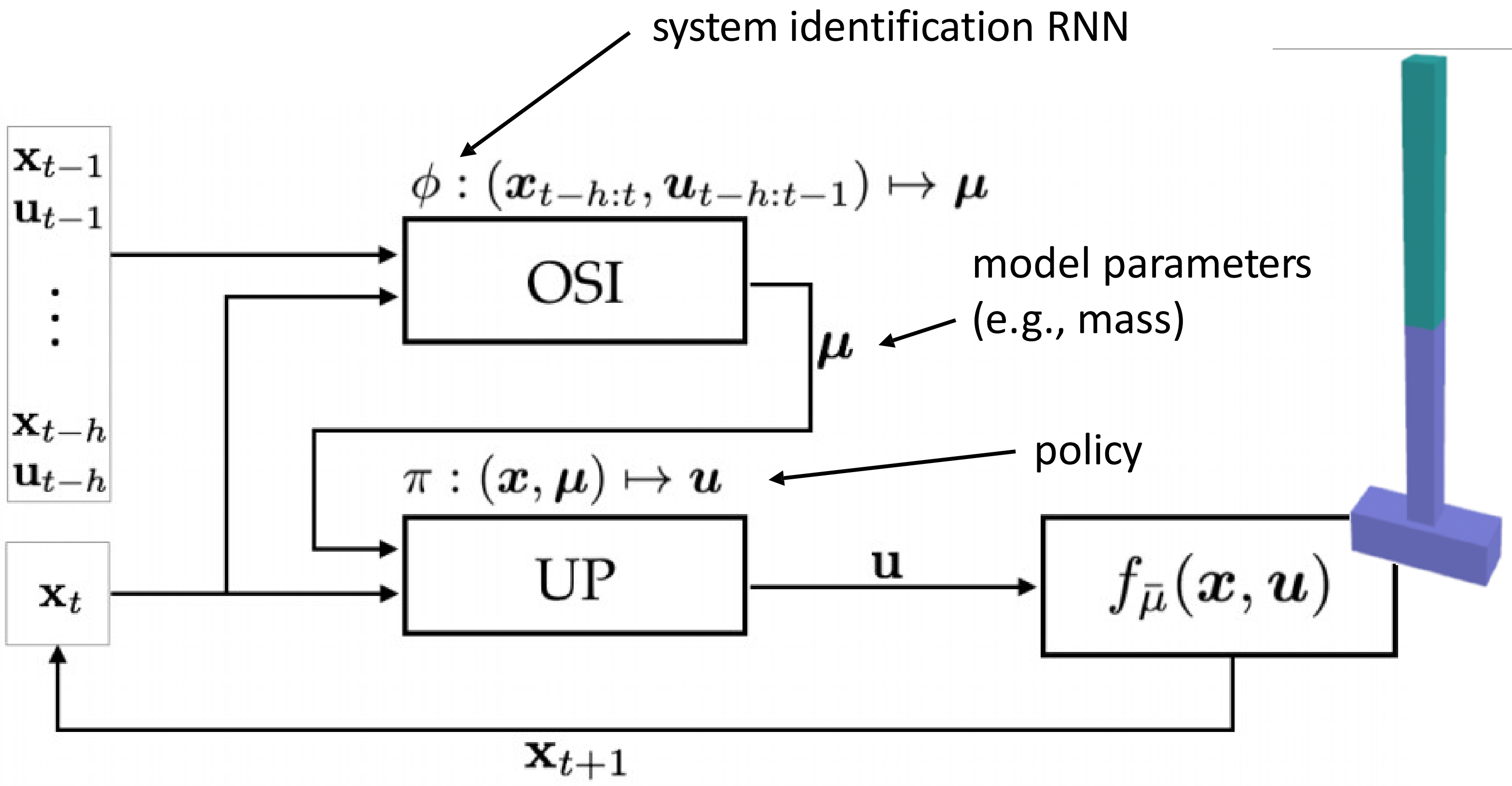


Hopper	μ	σ	low	high
~~mass~~	~~6.0~~	~~1.5~~	~~3.0~~	~~9.0~~
ground friction	2.0	0.25	1.5	2.5
joint damping	2.5	1.0	1.0	4.0
armature	1.0	0.25	0.5	1.5
Half-Cheetah	μ	σ	low	high
~~mass~~	~~6.0~~	~~1.5~~	~~3.0~~	~~9.0~~
ground friction	0.5	0.1	0.3	0.7
joint damping	1.5	0.5	0.5	2.5
armature	0.125	0.04	0.05	0.2



Rajeswaran et al., “EPOpt: Learning robust neural network policies…”

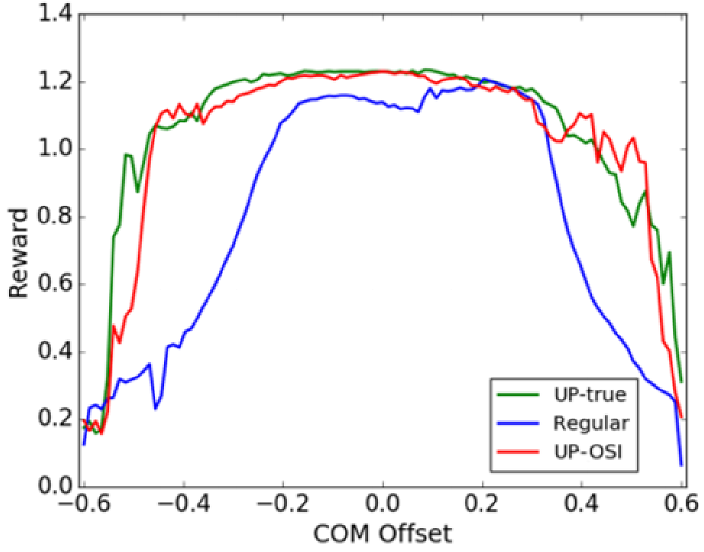
Preparing for the unknown: explicit system ID


$\mathbf{x}_{t-1}$
$\mathbf{u}_{t-1}$
$\vdots$
$\mathbf{x}_{t-h}$
$\mathbf{u}_{t-h}$
$\mathbf{x}_t$
$\phi : (\boldsymbol{x}_{t-h:t}, \boldsymbol{u}_{t-h:t-1}) \mapsto \boldsymbol{\mu}$
OSI
$\boldsymbol{\mu}$
$\pi : (\boldsymbol{x}, \boldsymbol{\mu}) \mapsto \boldsymbol{u}$
UP
$\mathbf{u}$
$f_{\bar{\mu}}(\boldsymbol{x}, \boldsymbol{u})$
$\mathbf{x}_{t+1}$

system identification RNN

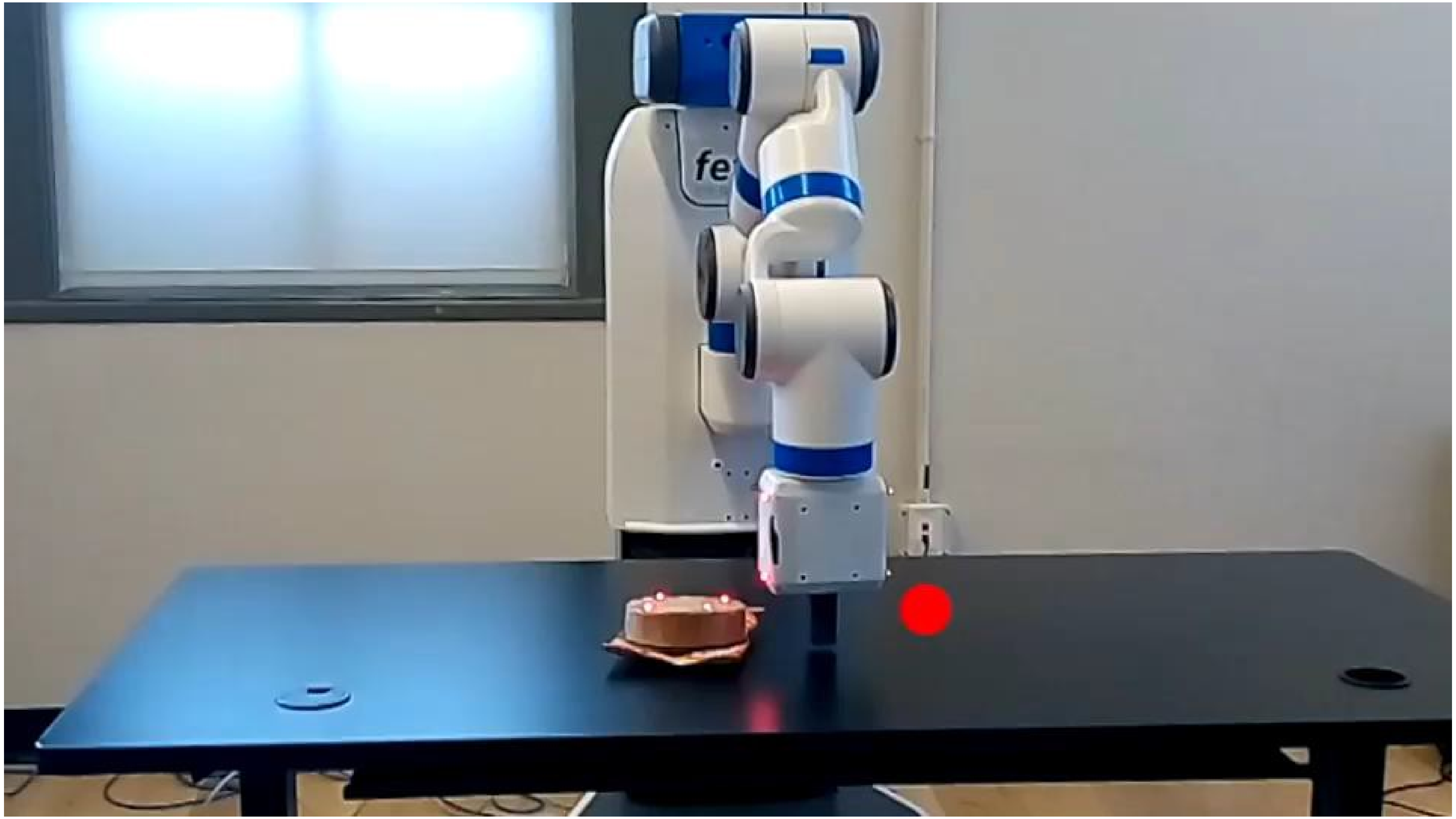
model parameters (e.g., mass)

policy



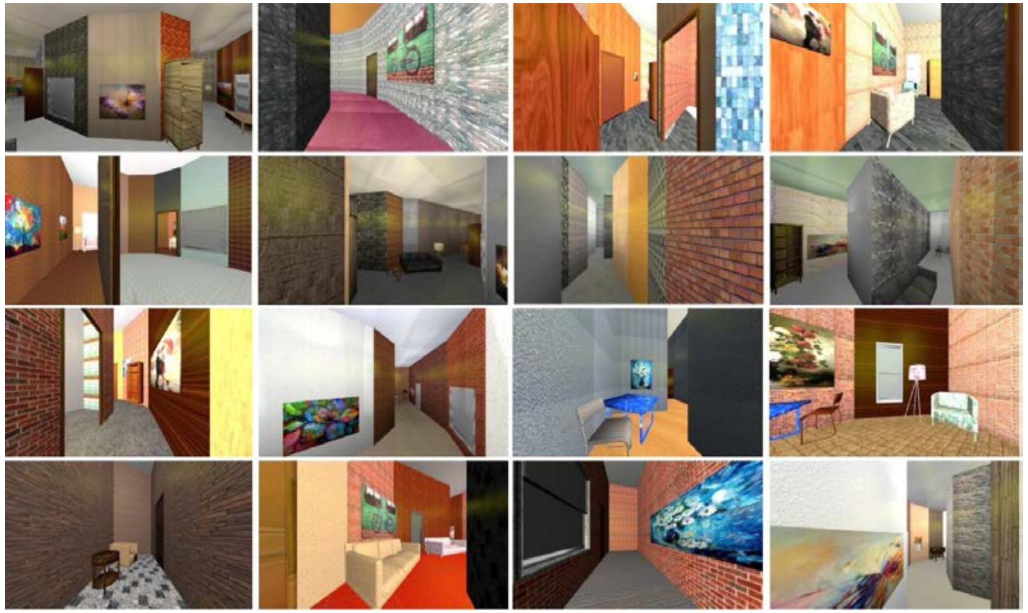
Yu et al., “Preparing for the Unknown: Learning a Universal Policy with Online System Identification”

Another example



Xue Bin Peng et al., “Sim-to-Real Transfer of Robotic Control with Dynamics Randomization”

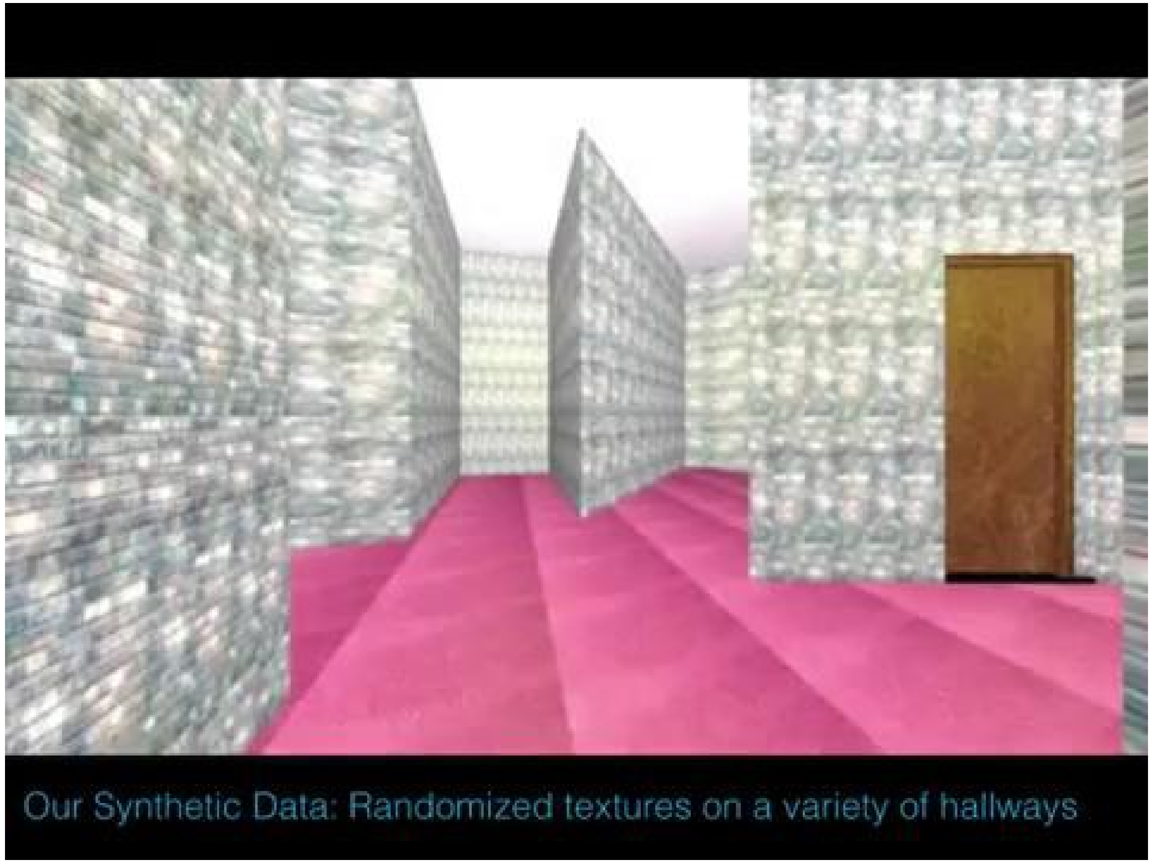
CAD2RL: randomization for real-world control



also called domain randomization

Sadeghi et al., “CAD2RL: Real Single-Image Flight without a Single Real Image”

CAD2RL: randomization for real-world control

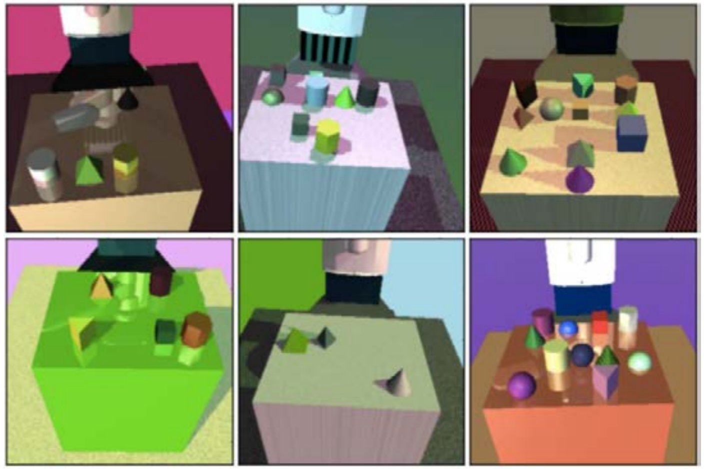


Our Synthetic Data: Randomized textures on a variety of hallways

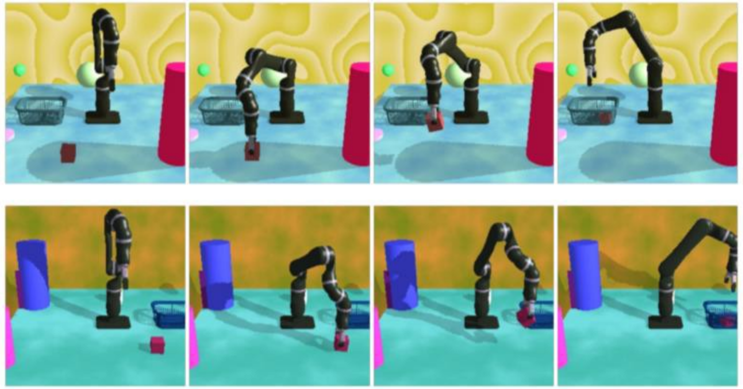
Sadeghi et al., “CAD2RL: Real Single-Image Flight without a Single Real Image”

Sadeghi et al., “CAD2RL: Real Single-Image Flight without a Single Real Image”

Randomization for manipulation



Tobin, Fong, Ray, Schneider, Zaremba, Abbeel



James, Davison, Johns

Source domain randomization and domain adaptation suggested readings

Rajeswaran, et al. (2017). **EPOpt: Learning Robust Neural Network Policies Using Model Ensembles.**

Yu et al. (2017). **Preparing for the Unknown: Learning a Universal Policy with Online System Identification.**

Sadeghi & Levine. (2017). **CAD2RL: Real Single Image Flight without a Single Real Image.**

Tobin et al. (2017). **Domain Randomization for Transferring Deep Neural Networks from Simulation to the Real World.**

James et al. (2017). **Transferring End-to-End Visuomotor Control from Simulation to Real World for a Multi-Stage Task.**

Methods that **also** incorporate domain adaptation together with randomization:

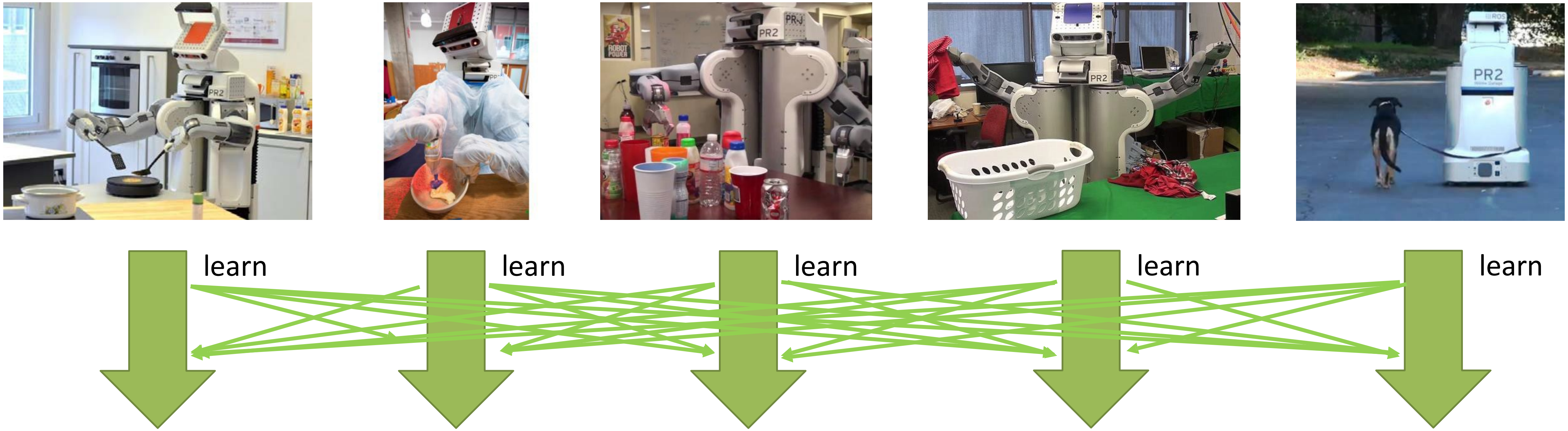
Bousmalis et al. (2017). **Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping.**

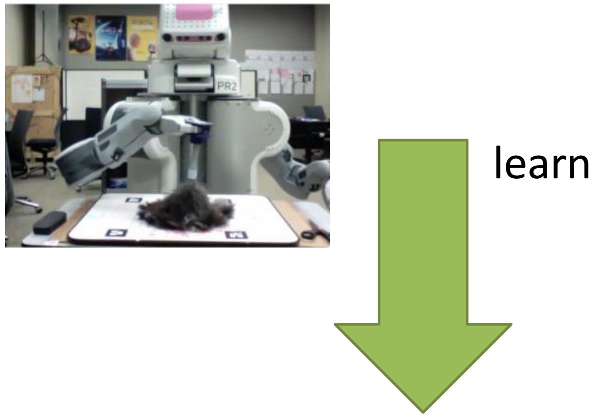
Rao et al. (2017). **RL-CycleGAN: Reinforcement Learning Aware Simulation-To-Real.**

… and many many others!

Multi-Task Transfer

Can we learn faster by learning multiple tasks?



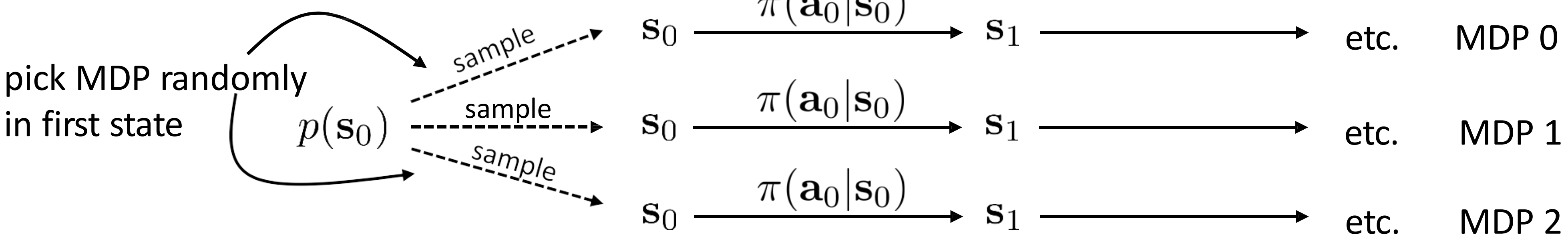


Multi-task learning can:

- Accelerate learning of all tasks that are learned together
- Provide better pre-training for down-stream tasks

Can we solve multiple tasks at once?

Multi-task RL corresponds to single-task RL in a **joint MDP**

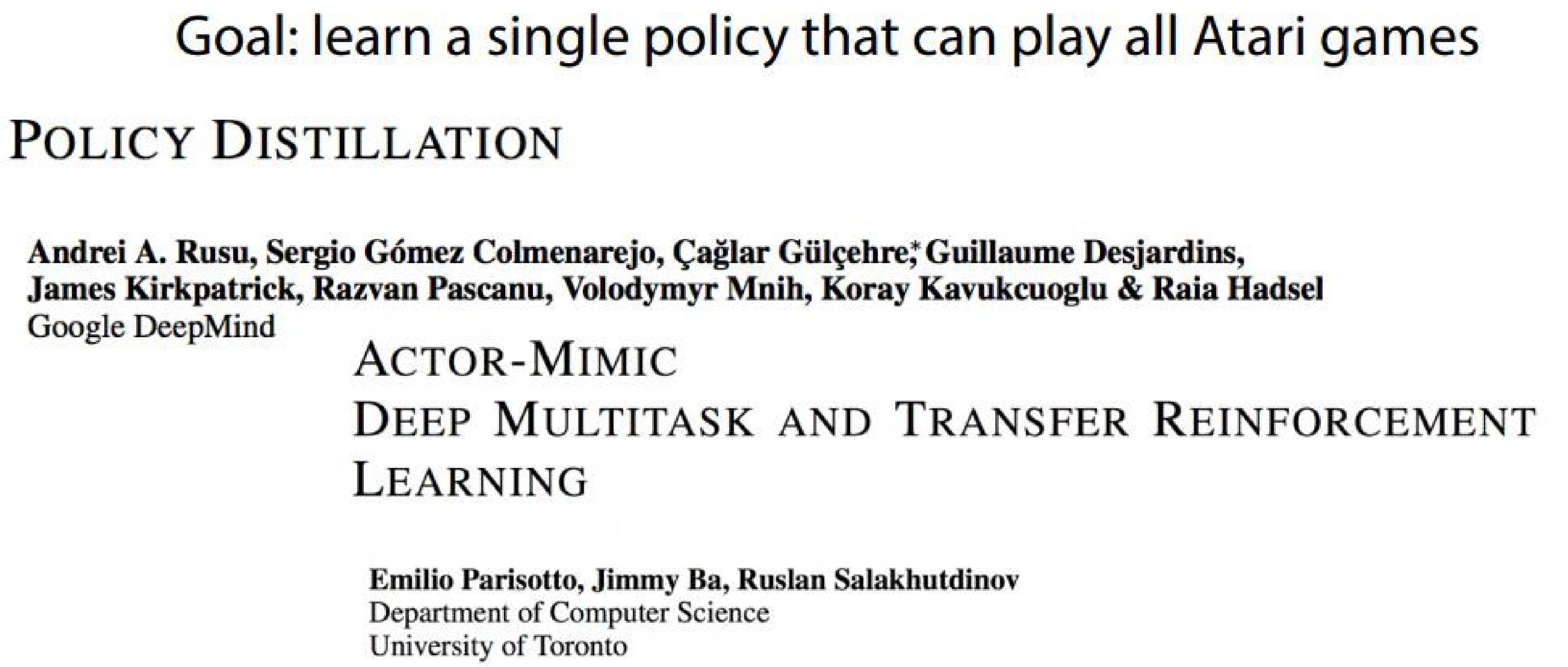


What is difficult about this?

- **Gradient interference:** becoming better on one task can make you worse on another
- **Winner-take-all problem:** imagine one task starts getting good – algorithm is likely to prioritize that task (to increase average expected reward) at the expensive of others

➢ In practice, this kind of multi-task RL is very challening

Actor-mimic and policy distillation



Goal: learn a single policy that can play all Atari games

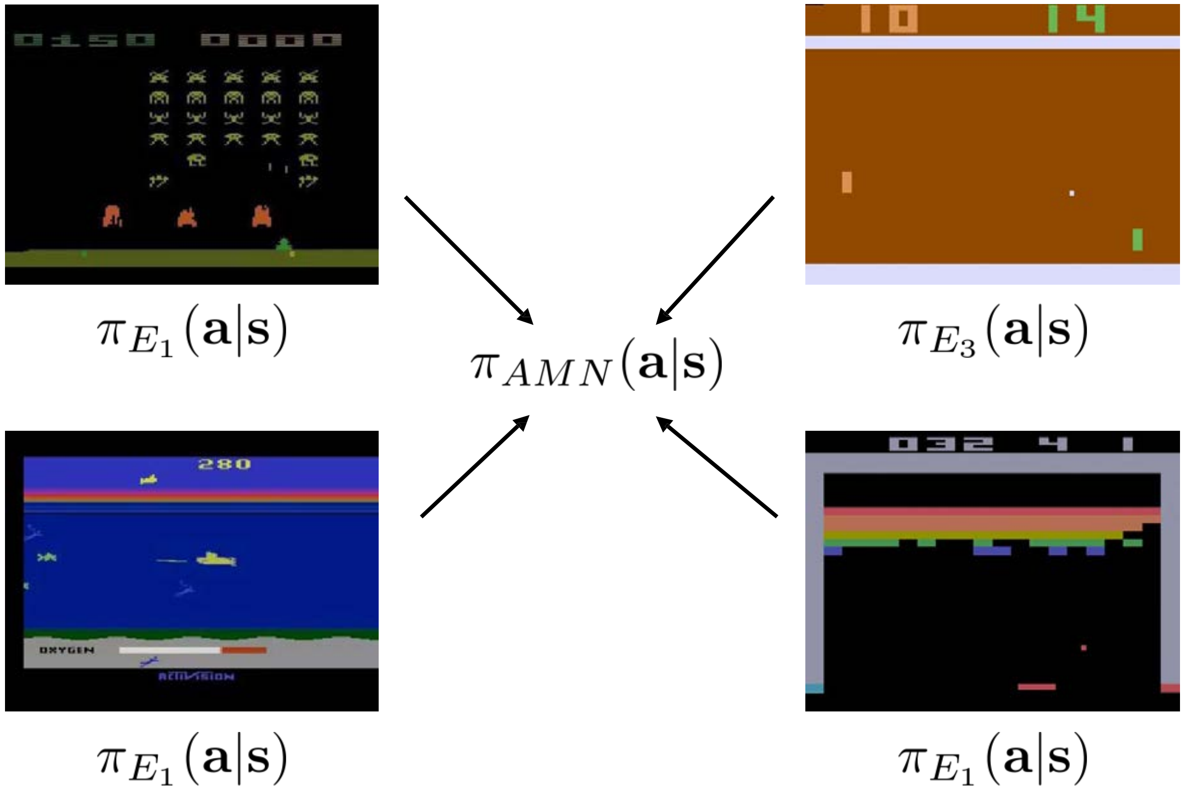
POLICY DISTILLATION

Andrei A. Rusu, Sergio Gómez Colmenarejo, Çağlar Gülçehre,* Guillaume Desjardins,
James Kirkpatrick, Razvan Pascanu, Volodymyr Mnih, Koray Kavukcuoglu & Raia Hadsel
Google DeepMind

ACTOR-MIMIC
DEEP MULTITASK AND TRANSFER REINFORCEMENT
LEARNING

Emilio Parisotto, Jimmy Ba, Ruslan Salakhutdinov
Department of Computer Science
University of Toronto

Distillation for Multi-Task Transfer



$\pi_{E_1}(\mathbf{a}|\mathbf{s})$

$\pi_{E_3}(\mathbf{a}|\mathbf{s})$

$\pi_{AMN}(\mathbf{a}|\mathbf{s})$

$\pi_{E_1}(\mathbf{a}|\mathbf{s})$

$\pi_{E_1}(\mathbf{a}|\mathbf{s})$

$$\mathcal{L} = \sum_{\mathbf{a}} \pi_{E_i}(\mathbf{a}|\mathbf{s}) \log \pi_{AMN}(\mathbf{a}|\mathbf{s})$$

(just supervised learning/distillation)

analogous to guided policy search, but for transfer learning

-> see model-based RL slides

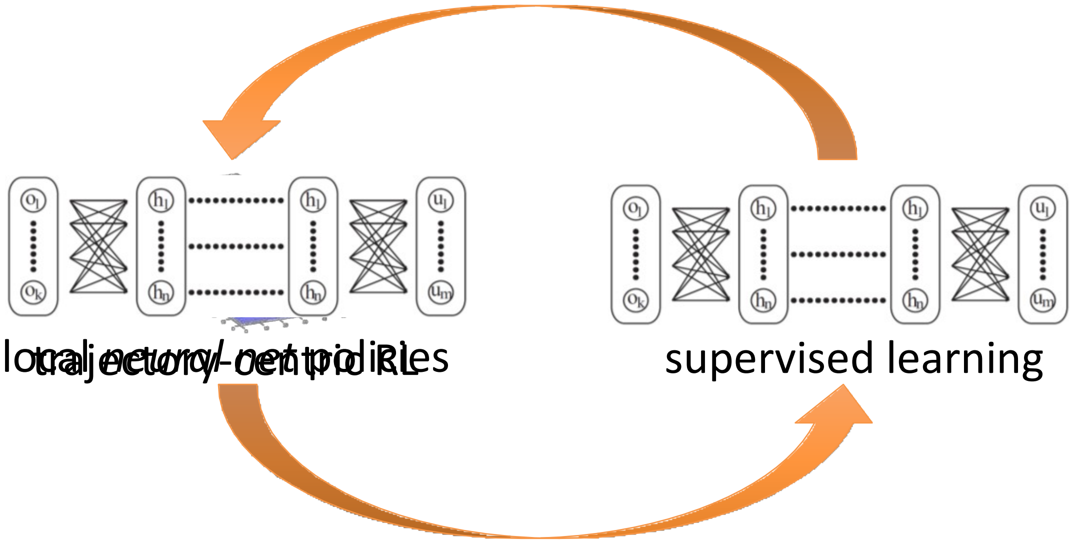
some other details

(e.g., feature regression objective)

– see paper

Parisotto et al. "Actor-Mimic: Deep Multitask and Transfer Reinforcement Learning"

Combining weak policies into a strong policy



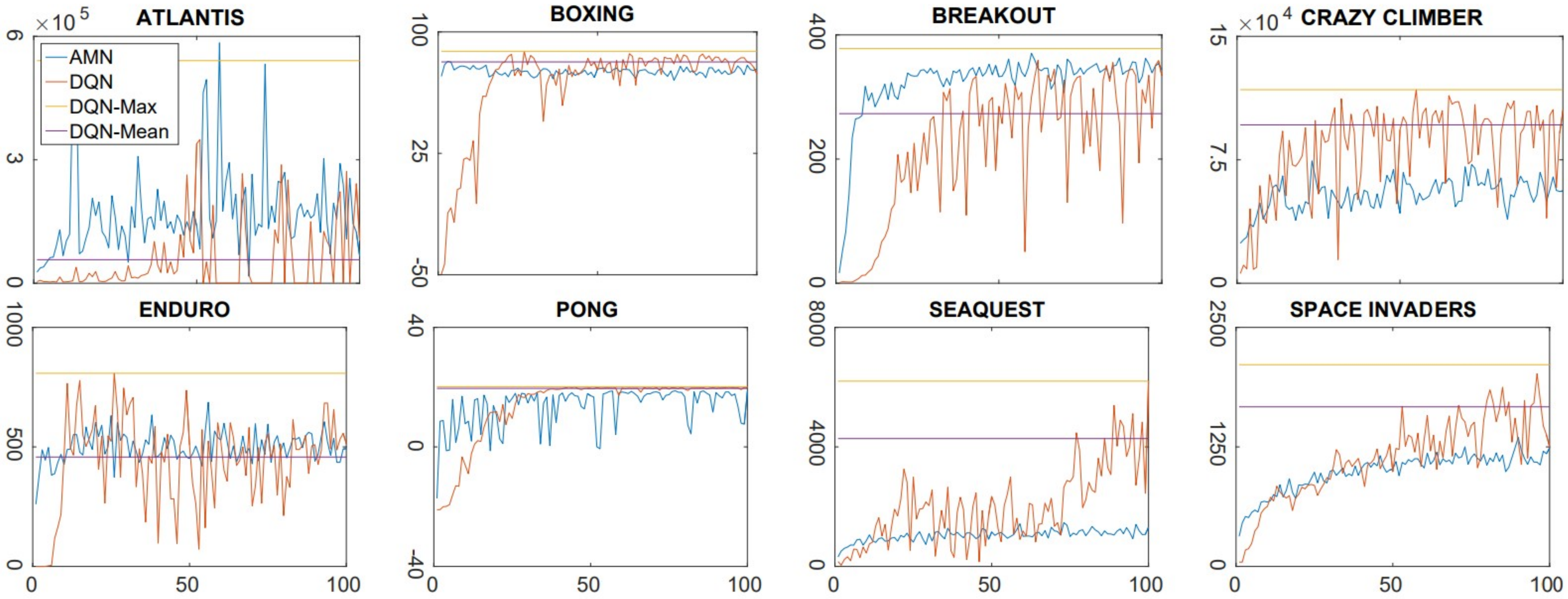
Divide and Conquer Reinforcement Learning

Divide and conquer reinforcement learning algorithm sketch:

1. optimize each local policy $\pi_{\theta_i}(\mathbf{a}_t|\mathbf{s}_t)$ on initial state $\mathbf{s}_{0,i}$ w.r.t. $\tilde{r}_{k,i}(\mathbf{s}_t, \mathbf{a}_t)$
2. use samples from step (1) to train $\pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$ to mimic each $\pi_{\theta_i}(\mathbf{u}_t|\mathbf{x}_t)$
3. update reward function $\tilde{r}_{k+1,i}(\mathbf{x}_t, \mathbf{u}_t) = r(\mathbf{x}_t, \mathbf{u}_t) + \lambda_{k+1,i} \log \pi_\theta(\mathbf{u}_t|\mathbf{x}_t)$

For details, see: “Divide and Conquer Reinforcement Learning”

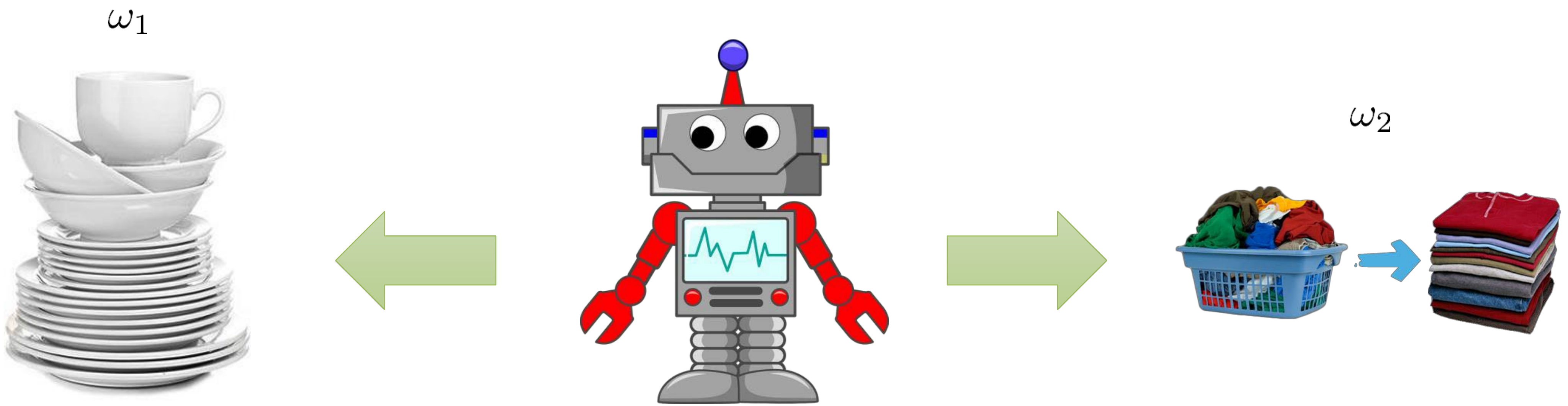
Distillation Transfer Results



Parisotto et al. "Actor-Mimic: Deep Multitask and Transfer Reinforcement Learning"

How does the model know what to do?

- So far: what to do is apparent from the input (e.g., which game is being played)
- What if the policy can do *multiple* things in the *same* environment?

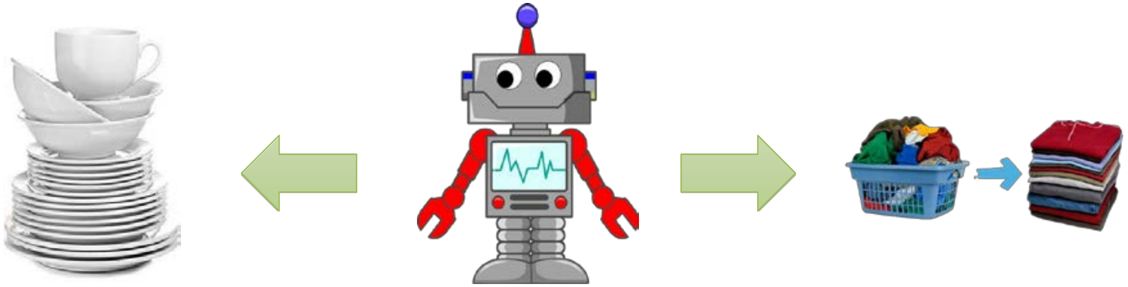


Contextual policies

standard policy: $\pi_\theta(\mathbf{a}|\mathbf{s})$

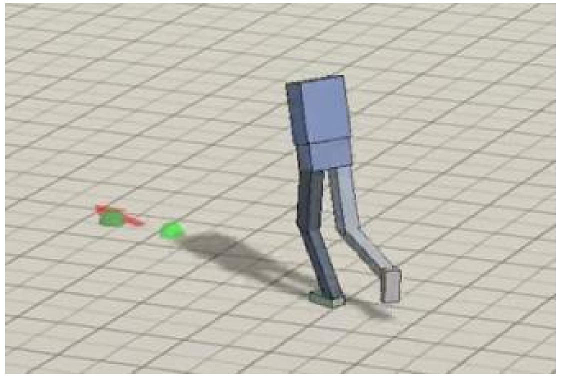
contextual policy: $\pi_\theta(\mathbf{a}|\mathbf{s}, \omega)$

e.g., do dishes or laundry

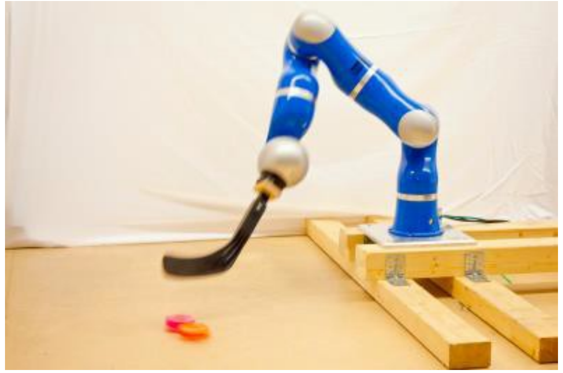


formally, simply defines augmented state space: $\tilde{\mathbf{s}} = \begin{bmatrix} \mathbf{s} \\ \omega \end{bmatrix}$ $\tilde{\mathcal{S}} = \mathcal{S} \times \Omega$

ω: stack location



ω: walking direction



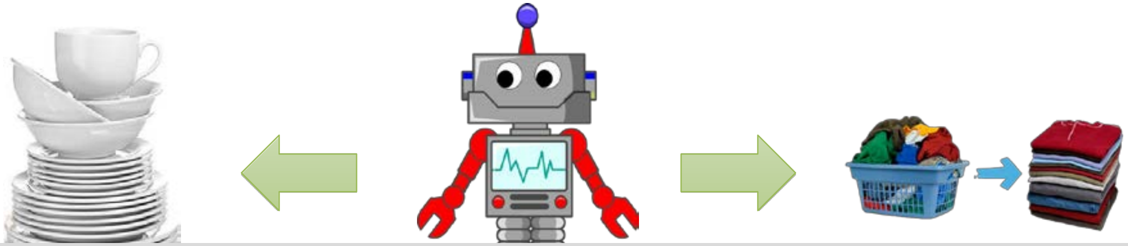
ω: where to hit puck

images: Peng, van de Panne, Peters

Contextual policies

standard policy: $\pi_\theta(\mathbf{a}|\mathbf{s})$

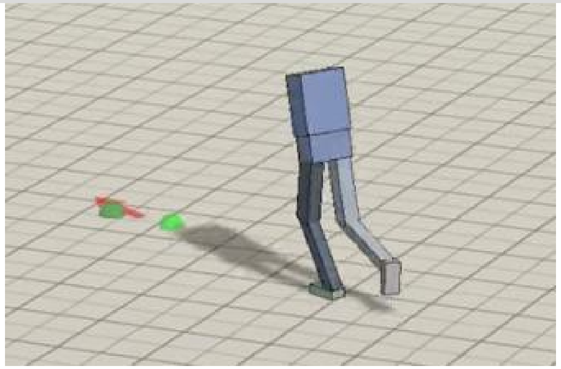
contextual policy: $\pi_\theta(\mathbf{a}|\mathbf{s}, \omega)$



will discuss more in the context of meta-learning!

forr

ω: stack location



ω: walking direction

ω: where to hit puck

images: Peng, van de Panne, Peters

Transferring Models and Value Functions

The problem setting

Assumption: the **dynamics** $p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$ is the same in both domains
but the **reward function** is different

Common setting:

- Autonomous car learns how to drive to a few destinations, and then has to navigate to a new one
- A kitchen robot learns to cook many different recipes, and then has to cook a new one in the same kitchen

What is the best object to transfer?

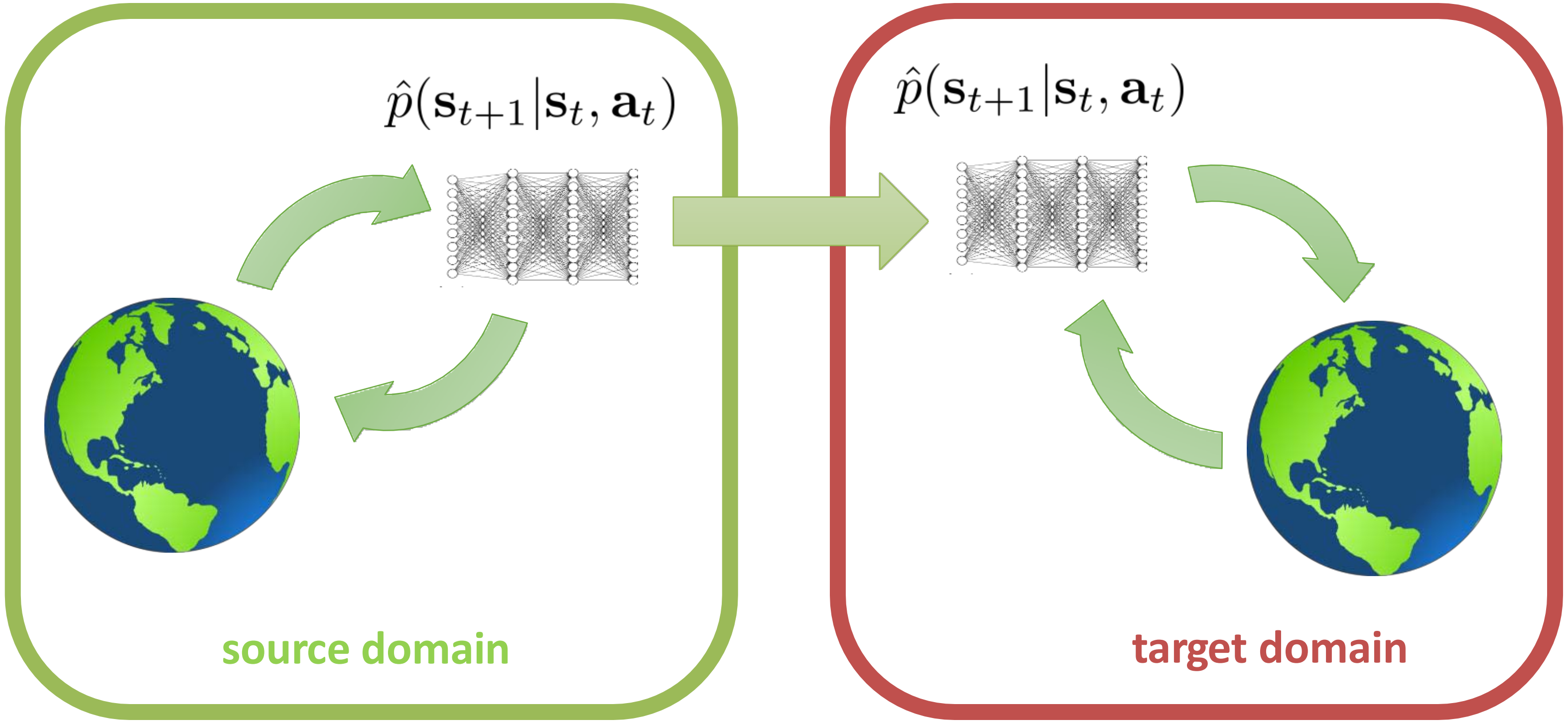
Model: very simple to transfer, since the model is already (in principle) independent of the reward

Value function: not straightforward to transfer by itself, since the value function entangles the dynamics and reward, but possible with a decomposition

- what kind of “dynamics relevant” information does a value function contain?

Policy: possible to do with contextual policies, but otherwise tricky, because the policy contains the *least* dynamics information

Transferring models


$\hat{p}(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$
$\hat{p}(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$
source domain
target domain

why might zero-shot transfer not always work?

Transferring value functions

Not so fast! Value functions couple dynamics, rewards, **and** policies!

$$Q^\pi(\mathbf{s},\mathbf{a}) = \underline{r(\mathbf{s},\mathbf{a})} + \gamma E_{\mathbf{s}'\underline{\sim p(\mathbf{s}'|\mathbf{s},\mathbf{a})},\mathbf{a}'\underline{\sim \pi(\mathbf{a}'|\mathbf{s}')}}[Q^\pi(\mathbf{s}',\mathbf{a}')]$$

Is this really such a good idea? **Yes, because of linearity**

Key observation: the value function is linear in the reward function

let $\mathbf{P}\mathbf{v}$ denote a vector $\mathbf{w}$ of length $|S||A|$ given by $\mathbf{w}(\mathbf{s},\mathbf{a}) = E_{\mathbf{s}'\sim p(\mathbf{s}'|\mathbf{s},\mathbf{a})}[\mathbf{v}(\mathbf{s}')]$

let $\mathbf{P}^\pi\mathbf{v}$ denote a vector $\mathbf{w}$ of length $|S||A|$ given by $\mathbf{w}(\mathbf{s},\mathbf{a}) = E_{\mathbf{s}'\sim p(\mathbf{s}'|\mathbf{s},\mathbf{a}),\mathbf{a}'\sim\pi(\mathbf{a}'|\mathbf{s}')}[\mathbf{v}(\mathbf{s}',\mathbf{a}')]$

$$\underset{\uparrow}{Q^\pi} = \underset{\uparrow}{r} + \gamma\mathbf{P}^\pi Q^\pi \qquad Q^\pi = (\mathbf{I} - \gamma\mathbf{P}^\pi)^{-1} r$$

vectors with $|S||A|$ entries

Successor representations & successor features

$Q^\pi = (\mathbf{I} - \gamma \mathbf{P}^\pi)^{-1} r$

let ϕ be a $|S||A| \times N$ *feature* matrix

let ψ be a $|S||A| \times N$ matrix such that $\psi = (\mathbf{I} - \mathbf{P}^\pi)^{-1} \phi$

if $r = \phi w$, then $Q^\pi = \psi w$

$1 \times N$ row vector

Proof: $Q^\pi = (\mathbf{I} - \gamma \mathbf{P}^\pi)^{-1} r$

$Q^\pi = (\mathbf{I} - \gamma \mathbf{P}^\pi)^{-1} \phi w$

$Q^\pi = \psi w$

ψ_i is a "successor feature" for ϕ_i

Successor representations & successor features

let ϕ be a $|S||A| \times N$ *feature* matrix

let ψ be a $|S||A| \times N$ matrix such that $\psi = (\mathbf{I} - \mathbf{P}^\pi)^{-1}\phi$

if $r = \phi w$, then $Q^\pi = \psi w$

For any *new* reward function, if we can fit $r \approx \phi w$, we get $Q^\pi \approx \psi w$

Important: this holds for Q^π, *not* $Q^\star$! why?

$$Q^\star(\mathbf{s}, \mathbf{a}) = r(\mathbf{s}, \mathbf{a}) + \gamma E_{\mathbf{s}' \sim p(\mathbf{s}'|\mathbf{s},\mathbf{a})}[\max_{\mathbf{a}'} Q^\pi(\mathbf{s}', \mathbf{a}')]$$

this is no longer linear!

Aside: successor representations

let ϕ be a $|S||A| \times N$ *feature* matrix

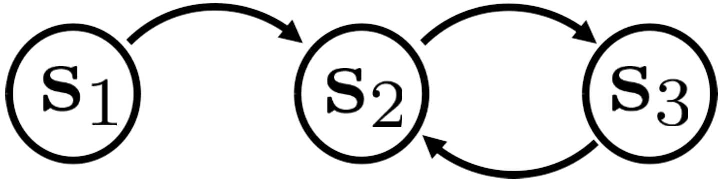
let ψ be a $|S||A| \times N$ matrix such that $\psi = (\mathbf{I} - \mathbf{P}^\pi)^{-1}\phi$

if $r = \phi w$, then $Q^\pi = \psi w$

what if $\phi = \mathbf{I}$? for each $(\mathbf{s}, \mathbf{a})$, there is a $\phi_{\mathbf{s},\mathbf{a}} = \delta(\mathbf{s}, \mathbf{a})$

then we can show that $\psi_{\mathbf{s}',\mathbf{a}'}(\mathbf{s}, \mathbf{a})$ predicts

probability of landing in $(\mathbf{s}', \mathbf{a}')$ from $(\mathbf{s}, \mathbf{a})$ under discount γ



$\gamma = 0.9$ $\psi_{\mathbf{s}_3}(\mathbf{s}_1) = 0.9^2$

Dayan. Improving generalization for temporal difference learning: The successor representation. 1993.

Transfer with successor features

Simplest use: evaluation

1. get small amount of data $(\mathbf{s}_i, \mathbf{a}_i, r_i, \mathbf{s}'_i)$ in new MDP
2. fit w such that $\phi(\mathbf{s}_i, \mathbf{a}_i)w \approx r_i$ (linear regression)
3. initialize $Q^\pi(\mathbf{s}, \mathbf{a}) = \psi(\mathbf{s}, \mathbf{a})w$
4. finetune π and Q^π with any RL method

More sophisticated use: train multiple ψ^{π_i} functions for different π_i

choose initial policy $\pi(\mathbf{s}) = \arg\max_{\mathbf{a}} \max_i \psi^{\pi_i}(\mathbf{s}, \mathbf{a})w$

this provides a *better* initial policy in general

For more details, see: Barreto et al., Successor Features for Transfer in Reinforcement Learning

Recap

No single solution! Survey of various recent research papers

1. Forward transfer: train on one task, transfer to a new task
   a) Transferring visual representations & domain adaptation
   b) Domain adaptation in reinforcement learning
   c) Randomization
2. Multi-task transfer: train on many tasks, transfer to a new task
   a) Sharing representations and layers across tasks in multi-task learning
   b) Contextual policies
   c) Optimization challenges for multi-task learning
   d) Algorithms
3. Transferring models and value functions
   a) Model-based RL as a mechanism for transfer
   b) Successor features & representations