Transfer and Multi-Task Learning

CS 294-112: Deep Reinforcement Learning

Sergey Levine

Class Notes

1. Two weeks until the project milestone!

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) Just try it and hope for the best
   b) Architectures for transfer: progressive networks
   c) Finetune on the new task
   d) Randomize source task domain
2. Multi-task transfer: train on many tasks, transfer to a new task
   a) Model-based reinforcement learning
   b) Model distillation
   c) Contextual policies
   d) Modular policy networks
3. Multi-task meta-learning: learn to learn from many tasks
   a) RNN-based meta-learning
   b) Gradient-based meta-learning

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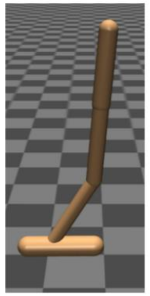
Finetuning summary

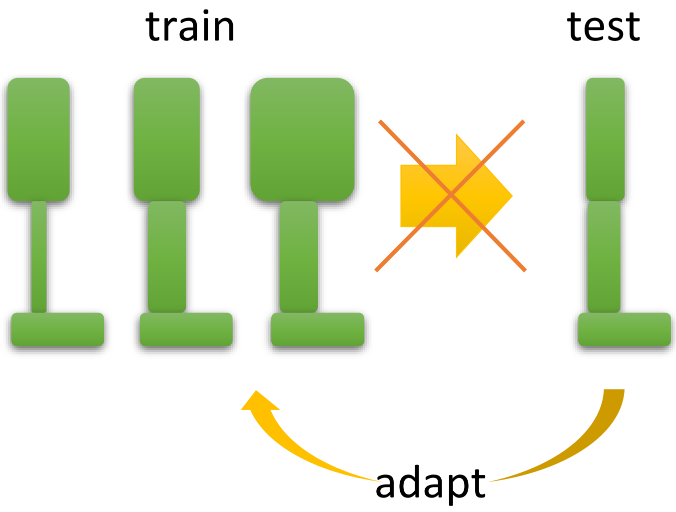
- Try and hope for the best
  - Sometimes there is enough variability during training to generalize
- Finetuning
  - A few issues with finetuning in RL
  - Maximum entropy training can help
- Architectures for finetuning: progressive networks
  - Addresses some overfitting and expressivity problems by construction

What if we can manipulate the source domain?

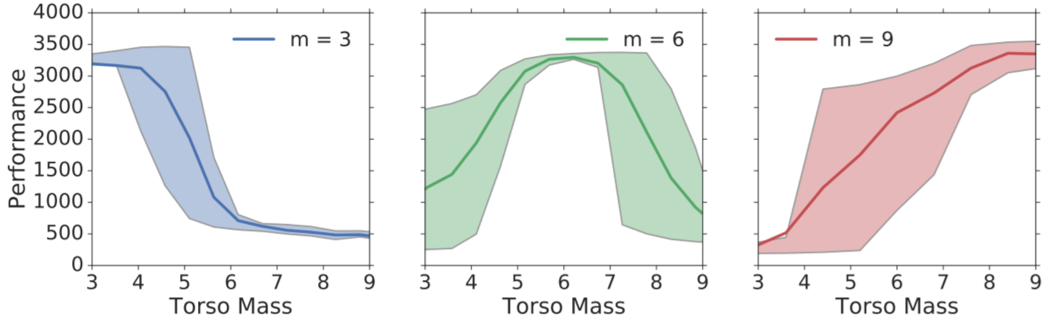
- So far: source domain (e.g., empty room) and target domain (e.g., corridor) are fixed
- What if we can **design** the source domain, and we have a **difficult** target domain?
  - Often the case for simulation to real world transfer
- Same idea: the more diversity we see at training time, the better we will transfer!

EPOpt: randomizing physical parameters

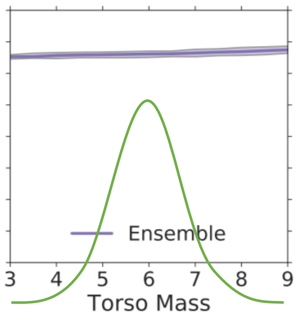




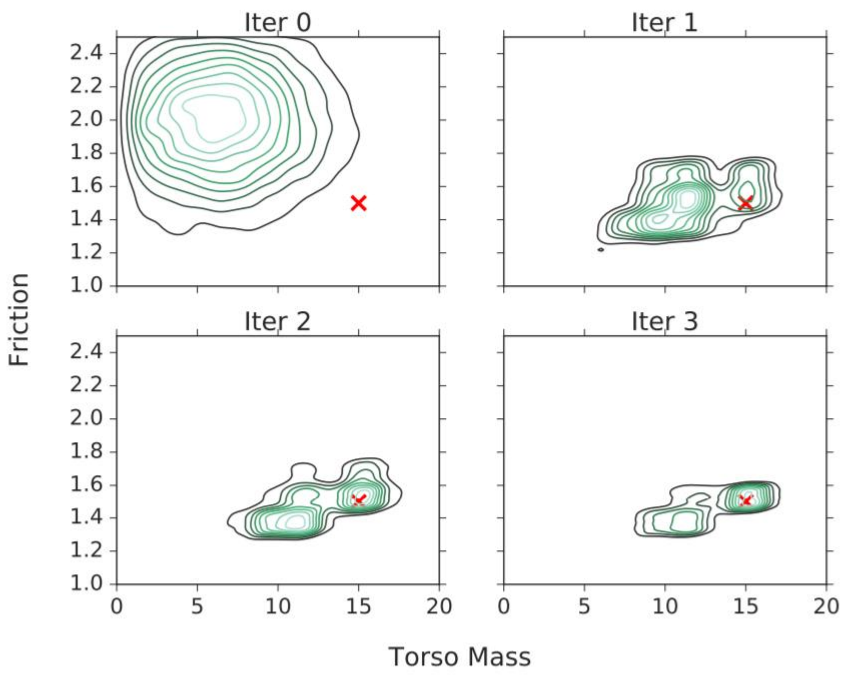
training on single torso mass



training on model ensemble

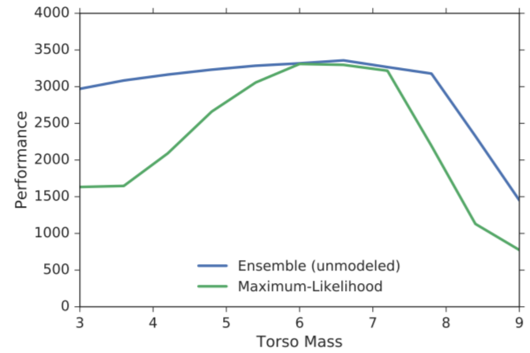


ensemble adaptation



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



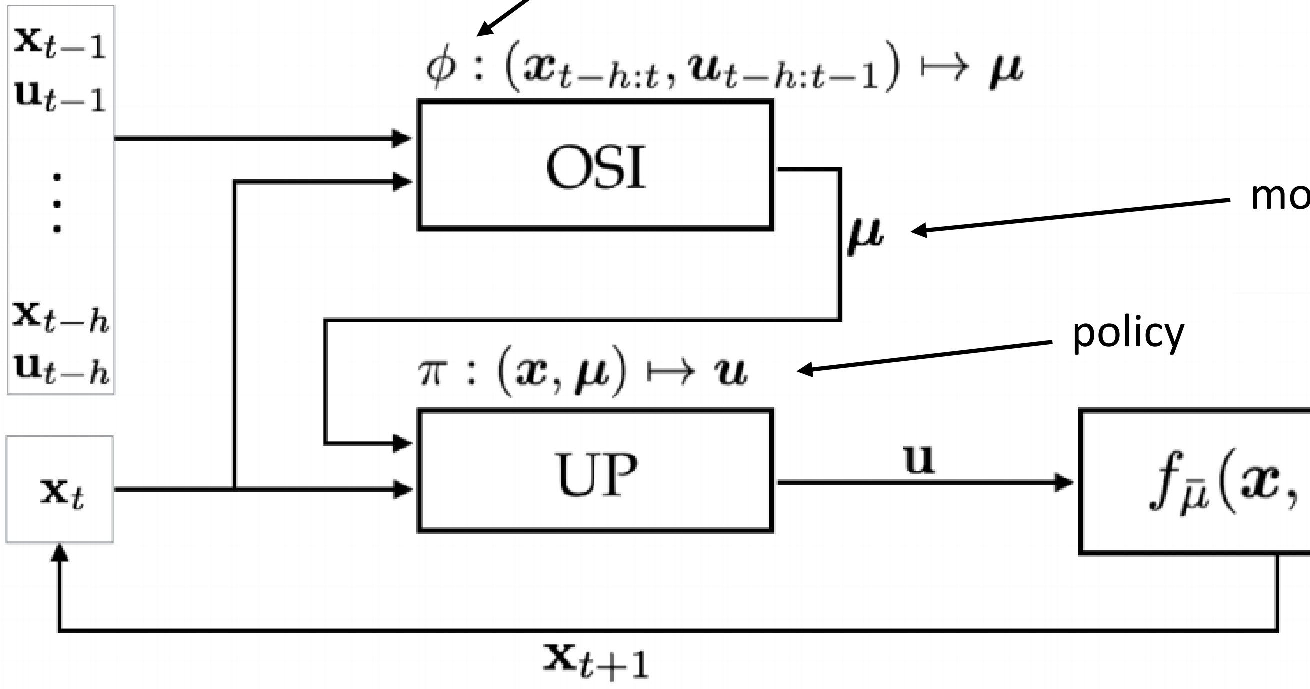
Rajeswaran et al., “EPOpt: Learning robust neural network policies…”

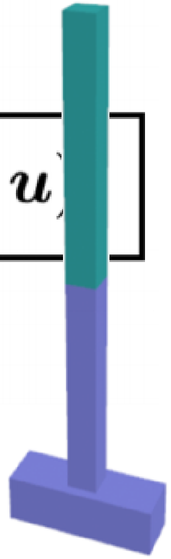
Preparing for the unknown: explicit system ID

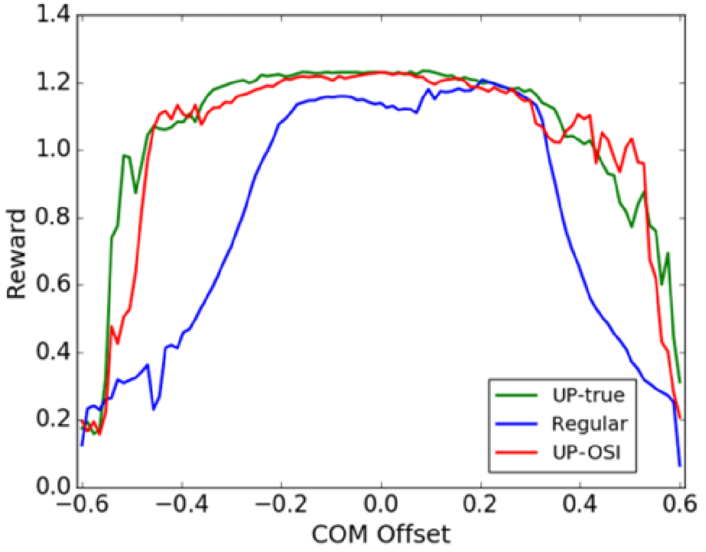
system identification RNN

model parameters (e.g., mass)

policy

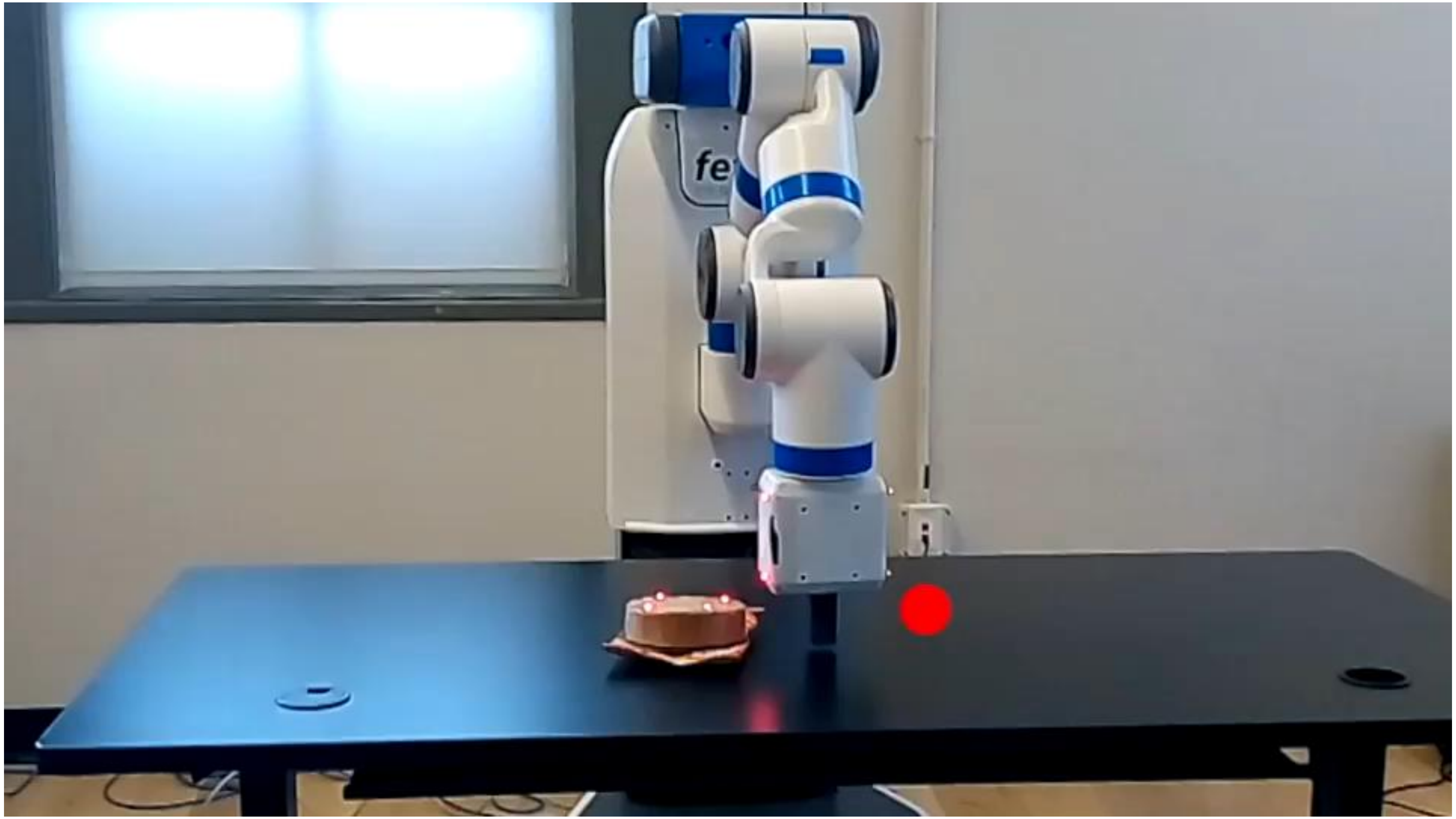






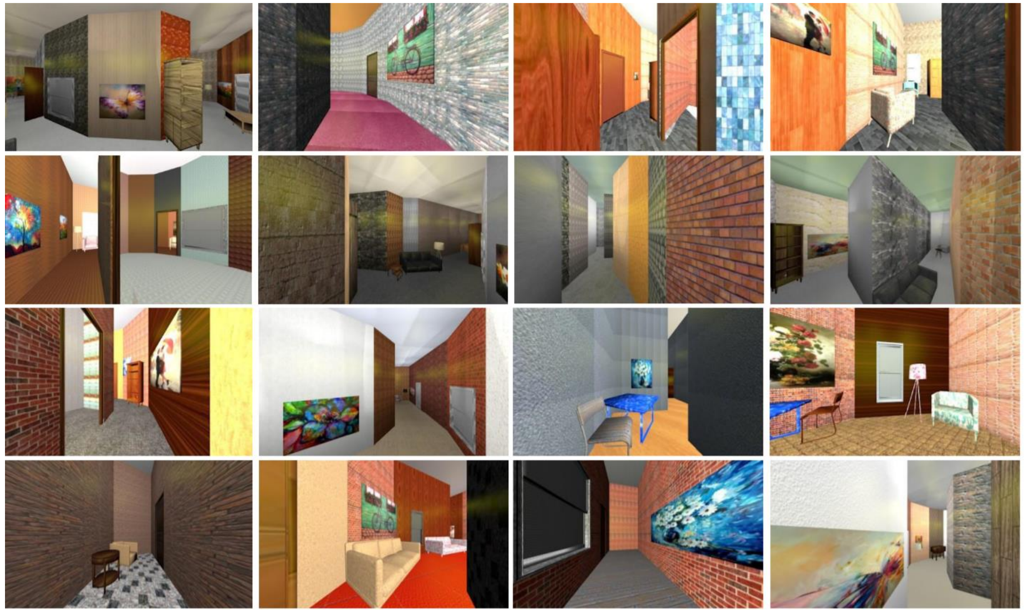
Yu et al., “Preparing for the Unknown: Learning a Universal Policy with Online System Identification”

(Very) recent work



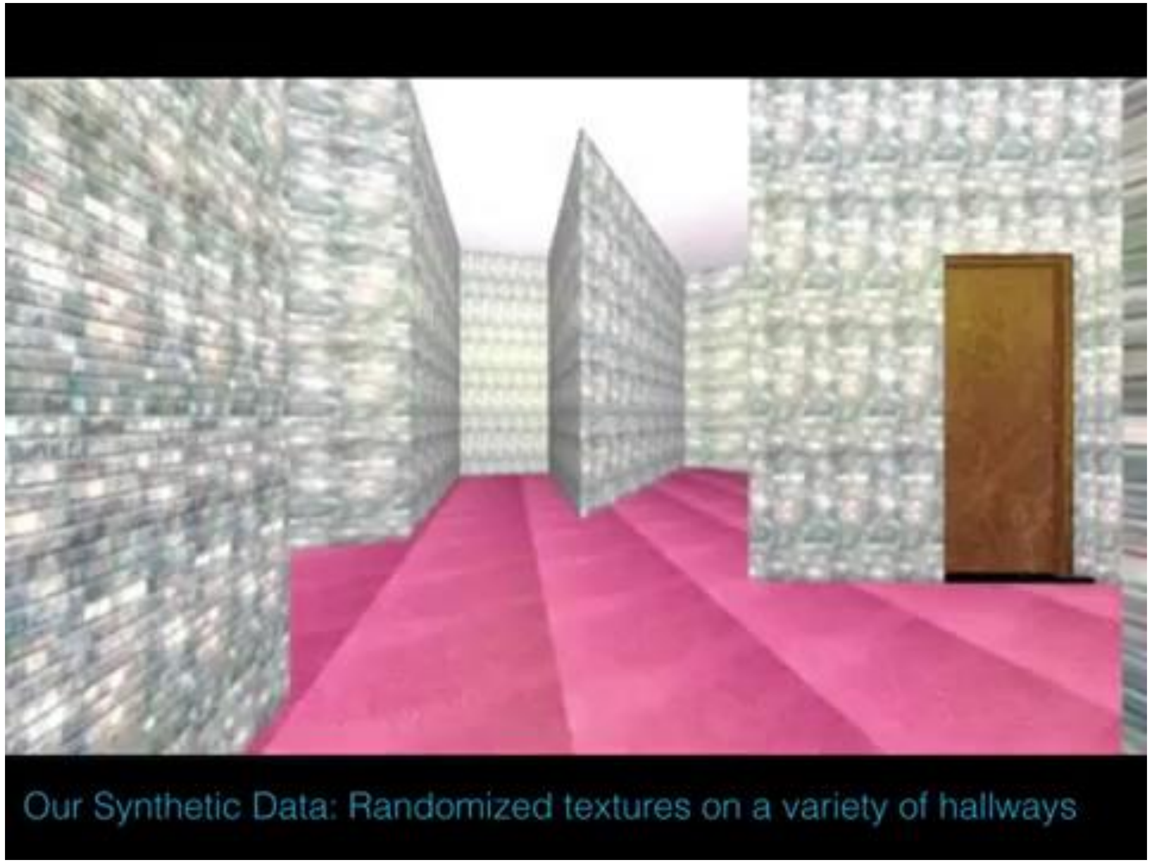
Xue Bin Peng et al., “Sim-to-Real Transfer of Robotic Control with Dynamics Randomization”

CAD2RL: randomization for real-world control



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

CAD2RL: randomization for real-world control



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

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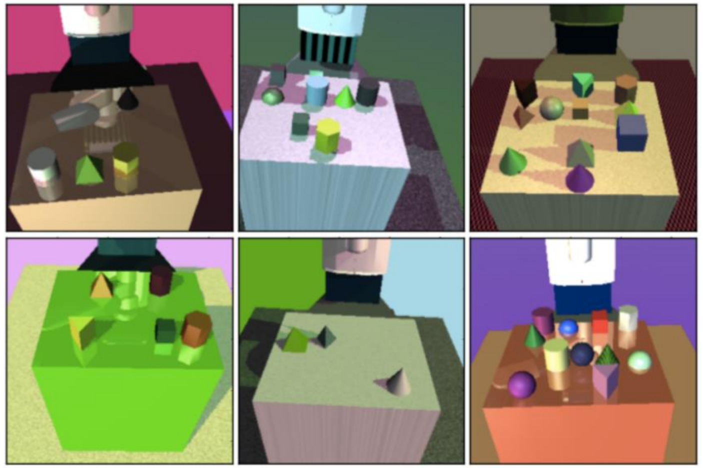
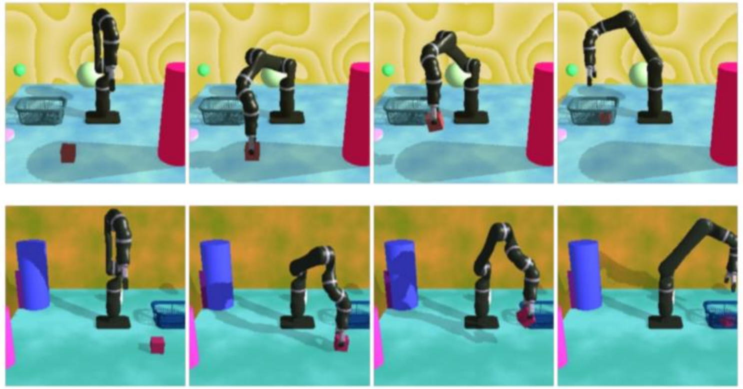
Randomization for manipulation



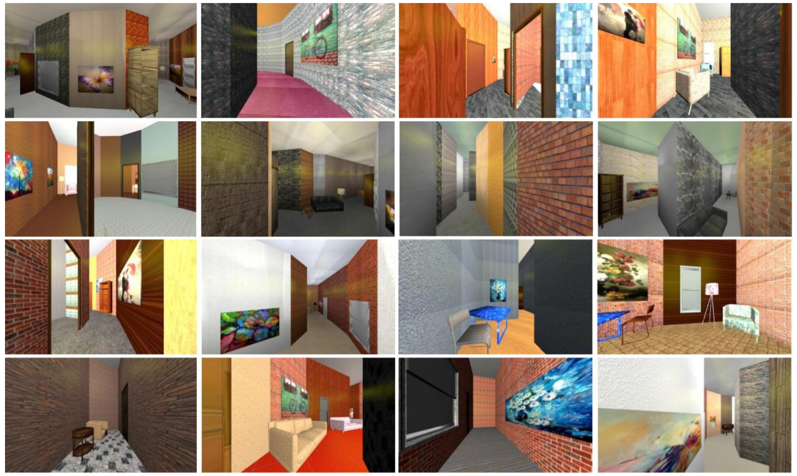
Tobin, Fong, Ray, Schneider, Zaremba, Abbeel



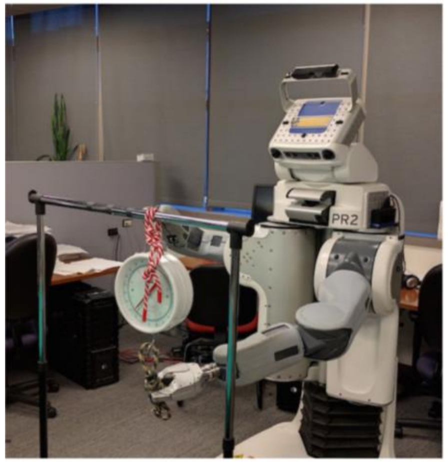
James, Davison, Johns

What if we can peek at the target domain?

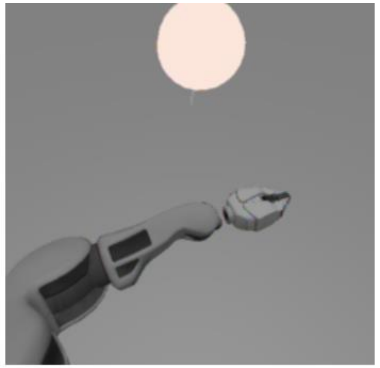
- So far: pure 0-shot transfer: learn in source domain so that we can succeed in **unknown** target domain
- Not possible in general: if we know nothing about the target domain, the best we can do is be as robust as possible
- What if we saw a few images of the target domain?



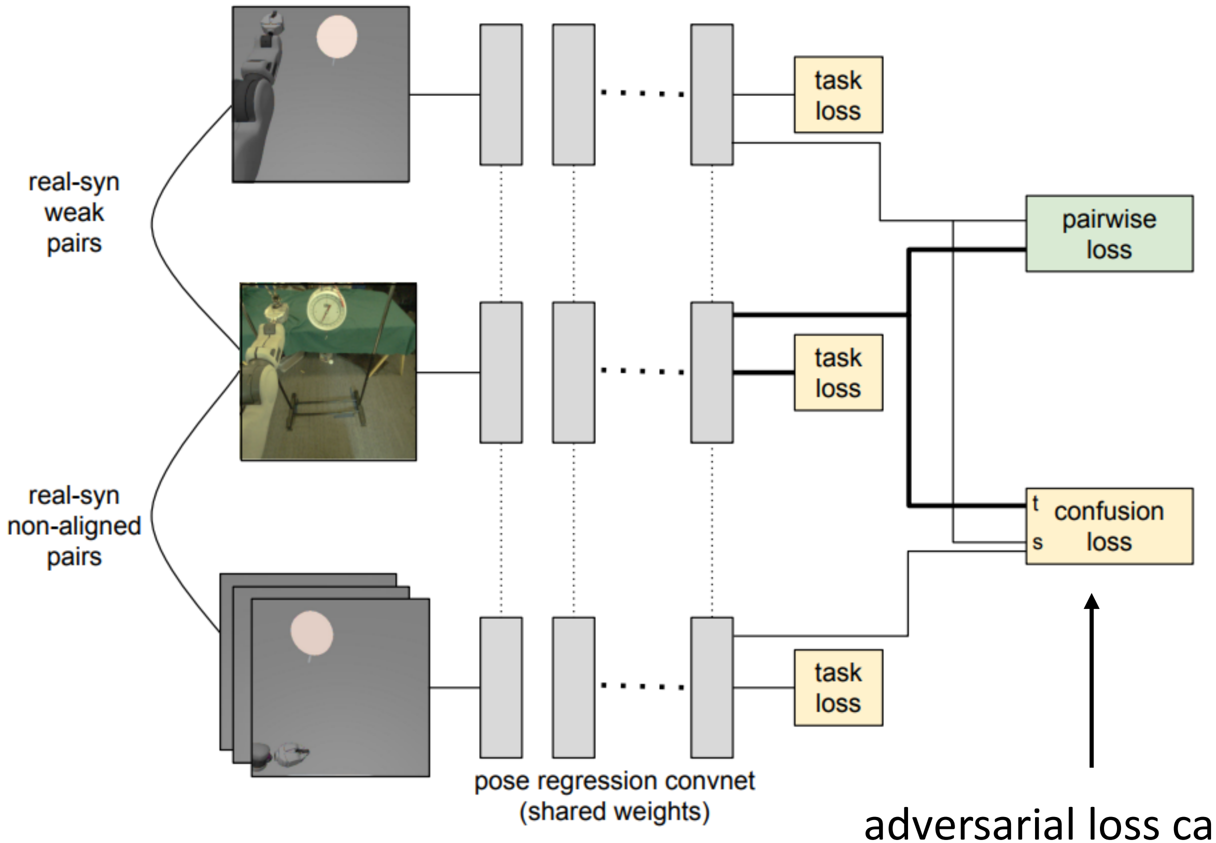
Better transfer through domain adaptation



simulated images



real images

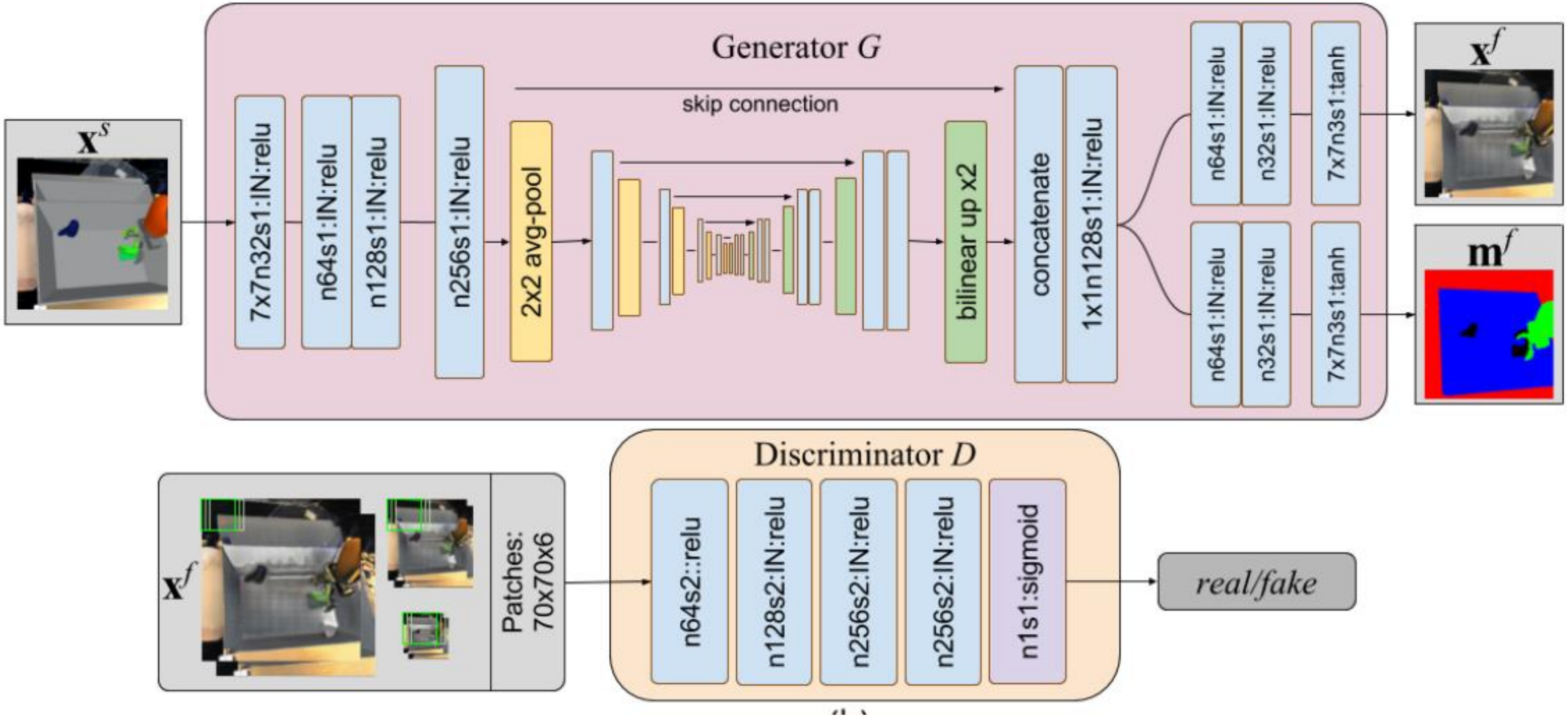


adversarial loss causes internal CNN features to be indistinguishable for sim and real

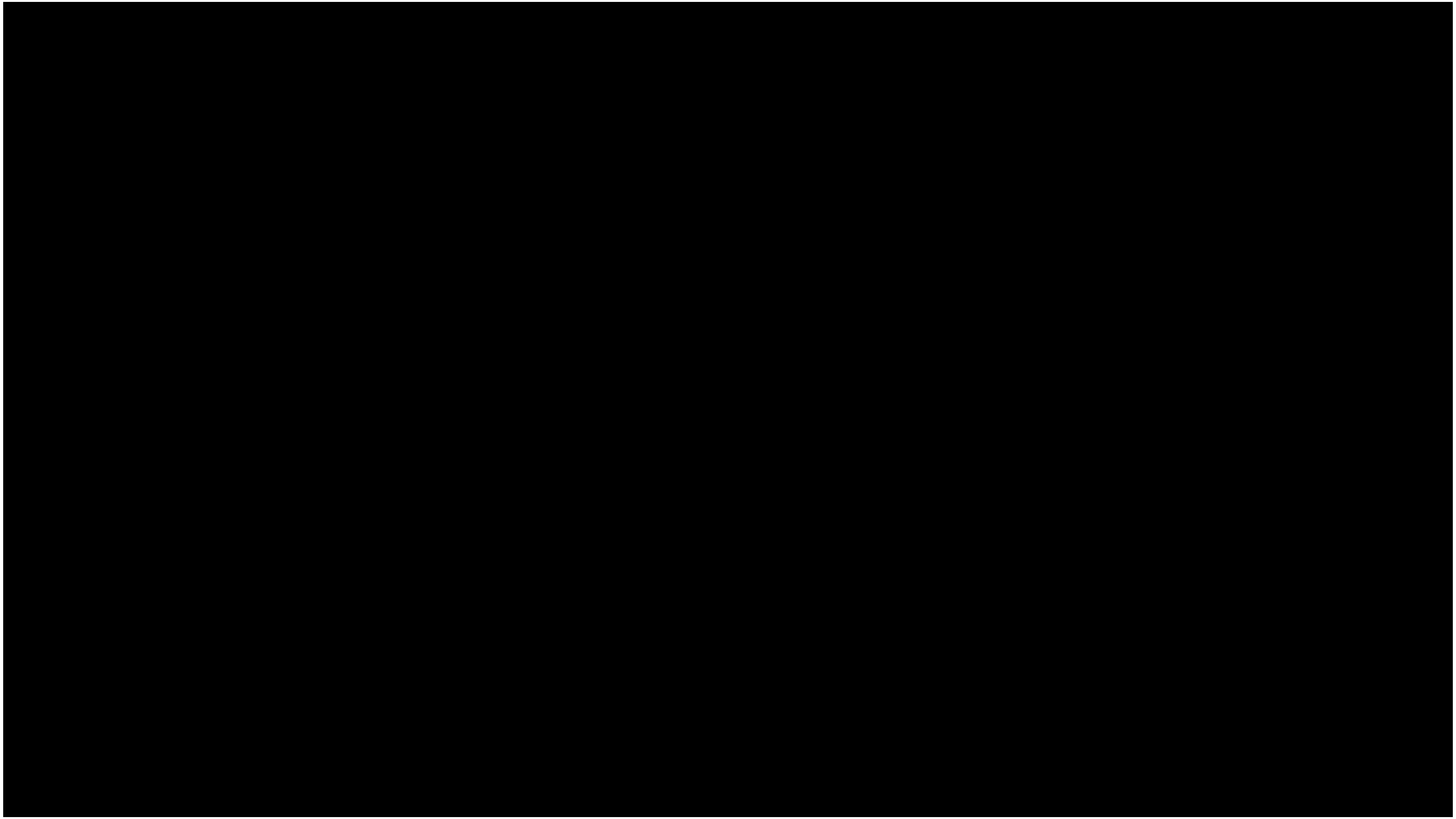
Tzeng*, Devin*, et al., "Adapting Visuomotor Representations with Weak Pairwise Constraints"

Domain adaptation at the pixel level

can we *learn* to turn synthetic images into *realistic* ones?



Bousmalis et al., "Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping"



Bousmalis et al., “Using Simulation and Domain Adaptation to Improve Efficiency of Deep Robotic Grasping”

Forward transfer summary

- Pretraining and finetuning
  - Standard finetuning with RL is hard
  - Maximum entropy formulation can help
- How can we modify the source domain for transfer?
  - Randomization can help a lot: the more diverse the better!
- How can we use modest amounts of target domain data?
  - Domain adaptation: make the network unable to distinguish observations from the two domains
  - …or modify the source domain observations to look like target domain
  - Only provides **invariance** – assumes all differences are functionally irrelevant; this is not always enough!

Forward transfer suggested readings

Haarnoja*, Tang*, Abbeel, Levine. (2017). **Reinforcement Learning with Deep Energy-Based Policies.**

Rusu et al. (2016). **Progress Neural Networks.**

Rajeswaran, Ghotra, Levine, Ravindran. (2017). **EPOpt: Learning Robust Neural Network Policies Using Model Ensembles.**

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

Tobin, Fong, Ray, Schneider, Zaremba, Abbeel. (2017). **Domain Randomization for Transferring Deep Neural Networks from Simulation to the Real World.**

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

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

Break

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Multiple source domains

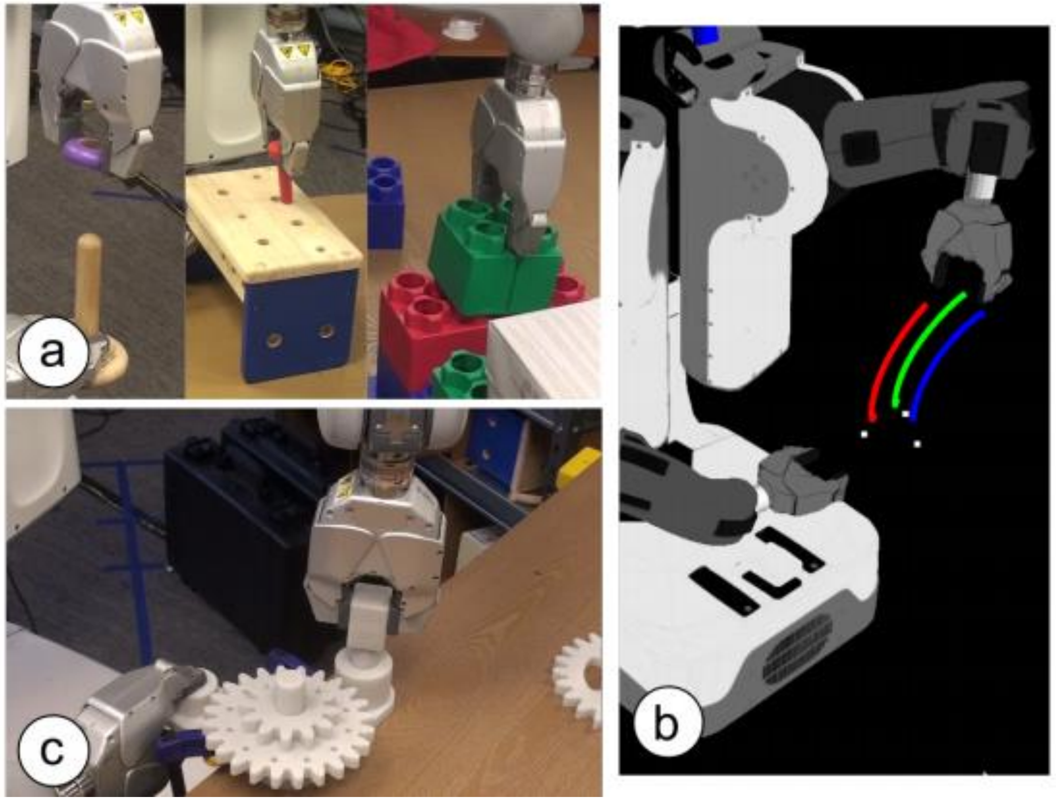
- So far: more diversity = better transfer
- Need to design this diversity
    - E.g., simulation to real world transfer: randomize the simulation
- What if we transfer from multiple *different* tasks?
    - In a sense, closer to what people do: build on a lifetime of experience
    - Substantially harder: past tasks don’t directly tell us how to solve the task in the target domain!

Model-based reinforcement learning

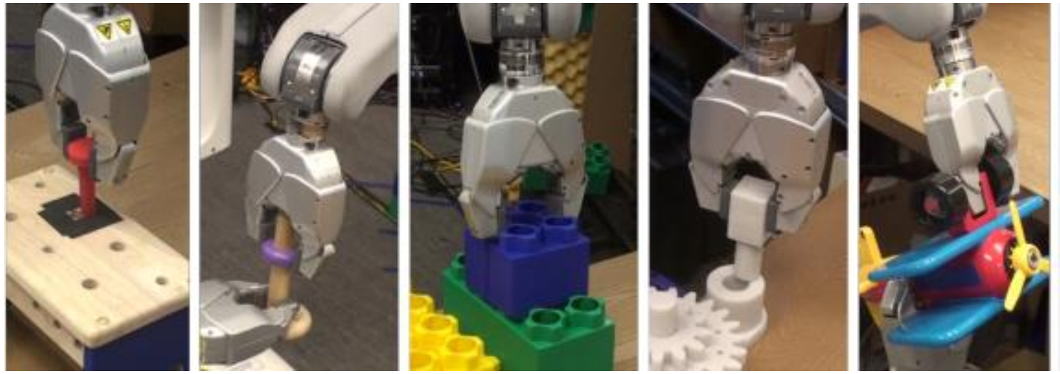
- If the past tasks are all different, what do they have in common?
- Idea 1: the laws of physics
  - Same robot doing different chores
  - Same car driving to different destinations
  - Trying to accomplish different things in the same open-ended video game
- Simple version: train model on past tasks, and then use it to solve new tasks
- More complex version: adapt or finetune the model to new task
  - Easier than finetuning the policy is task is very different but physics are mostly the same

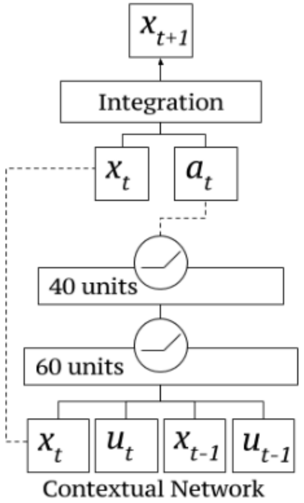
Model-based reinforcement learning

Example: 1-shot learning with model priors



Fu et al., “One-Shot Learning of Manipulation Skills with Online Dynamics Adaptation…”





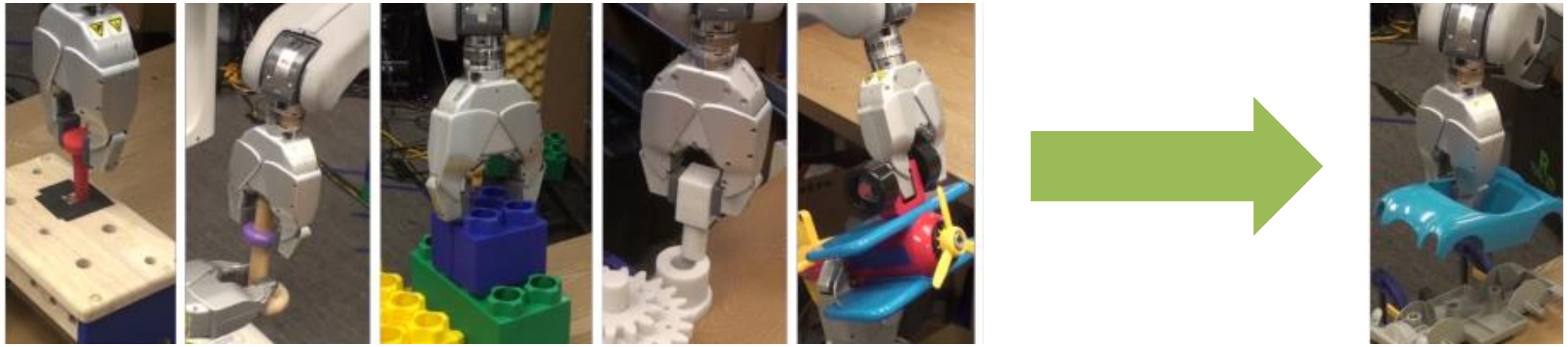
prior:
$\mathbf{\Phi}$, μ_0

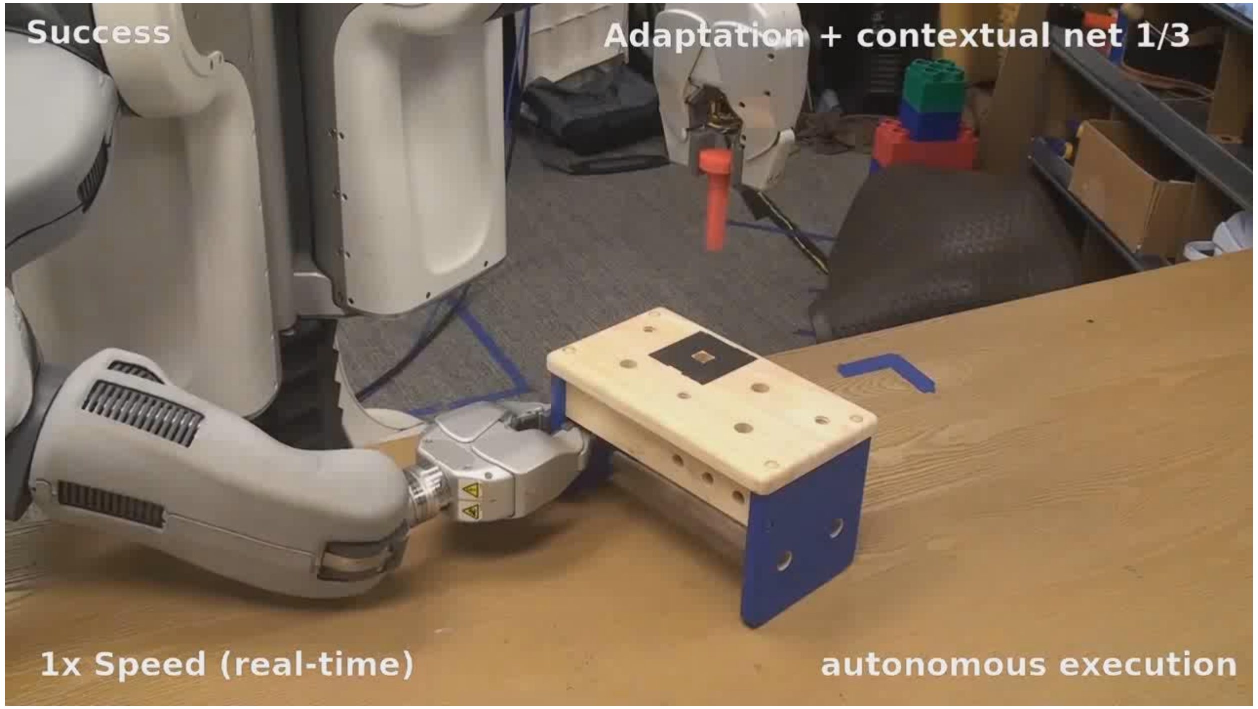
empirical estimate:
$\hat{\Sigma}$, $\hat{\mu}$

recent experience
$(\mathbf{x}_t, \mathbf{u}_t, \mathbf{x}_{t+1})$

posterior:
Σ, μ

Fu et al., “One-Shot Learning of Manipulation Skills with Online Dynamics Adaptation…”





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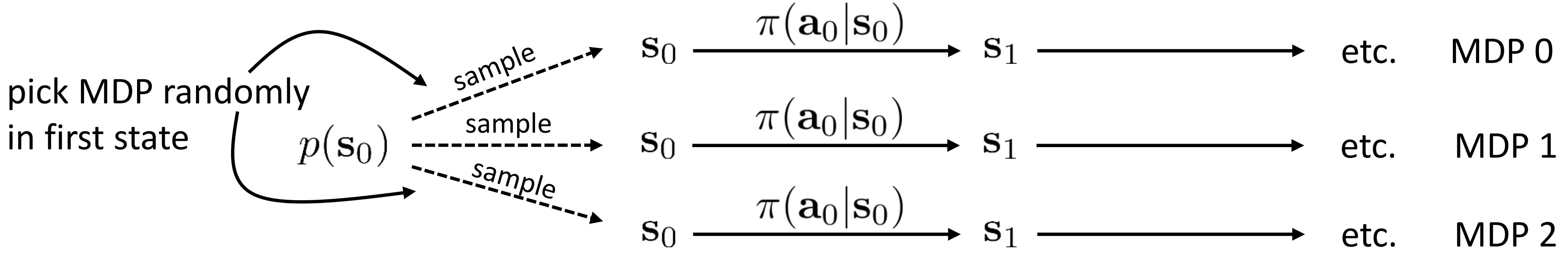
Can we solve multiple tasks at once?

- Sometimes learning a model is very hard
- Can we learn a multi-task policy that can *simultaneously* perform many tasks?
- Should be *easier* to adapt to new tasks
- Idea 1: construct a joint MDP



- Idea 2: train in each MDP separately, and then combine the policies

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

Background: Ensembles & Distillation

Ensemble models: single models are often not the most robust – instead train many models and average their predictions

this is how most ML competitions (e.g., Kaggle) are won

this is very expensive at test time

Can we make a single model that is as good as an ensemble?

Distillation: train on the ensemble's predictions as "soft" targets

logit

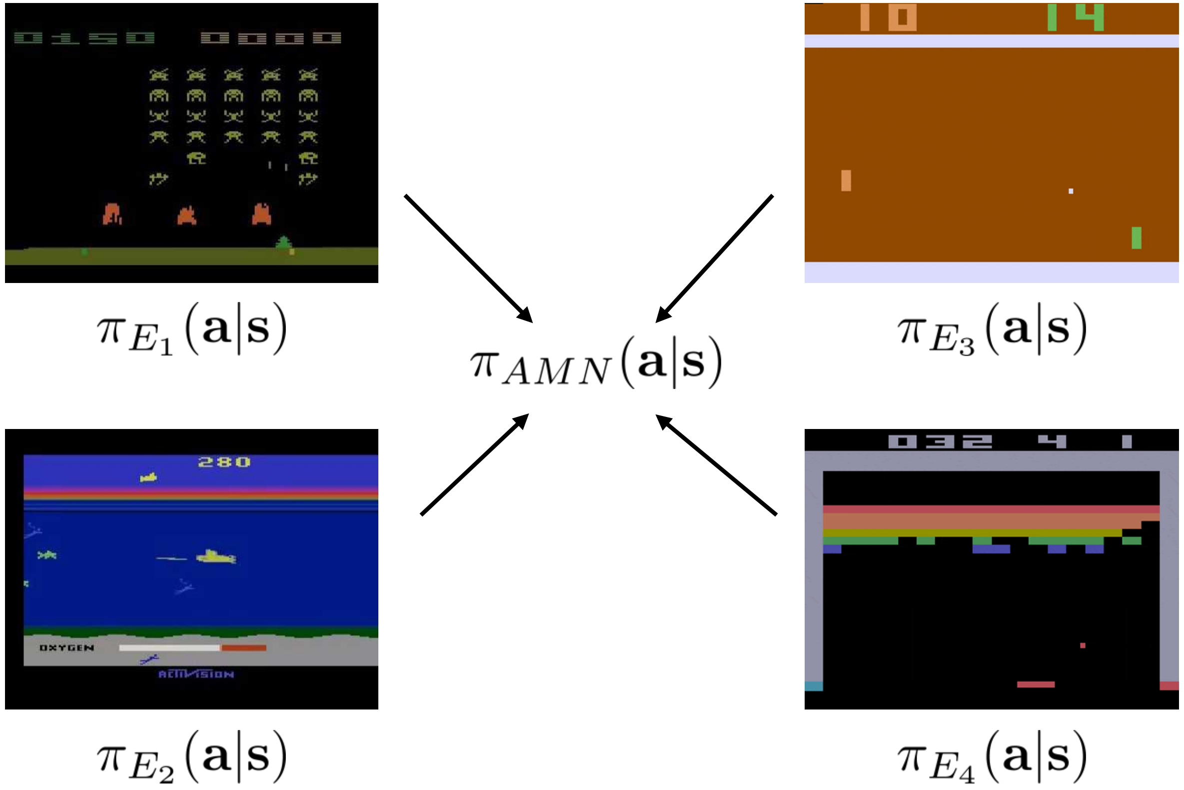
$$p_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$$

temperature

Intuition: more knowledge in soft targets than hard labels!

Slide adapted from G. Hinton, see also Hinton et al. "Distilling the Knowledge in a Neural Network"

Distillation for Multi-Task Transfer



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

(just supervised learning/distillation)

analogous to guided policy search, but for transfer learning

-> see model-based RL slides

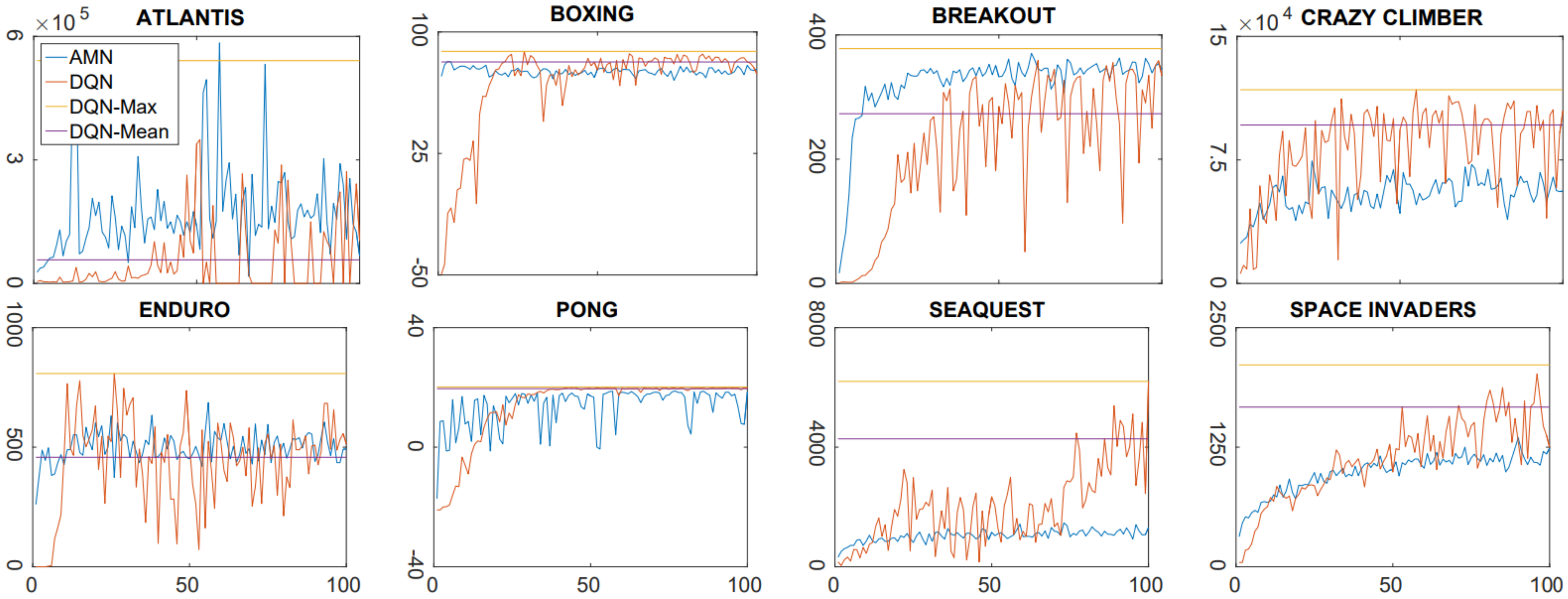
some other details

(e.g., feature regression objective)

– see paper

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

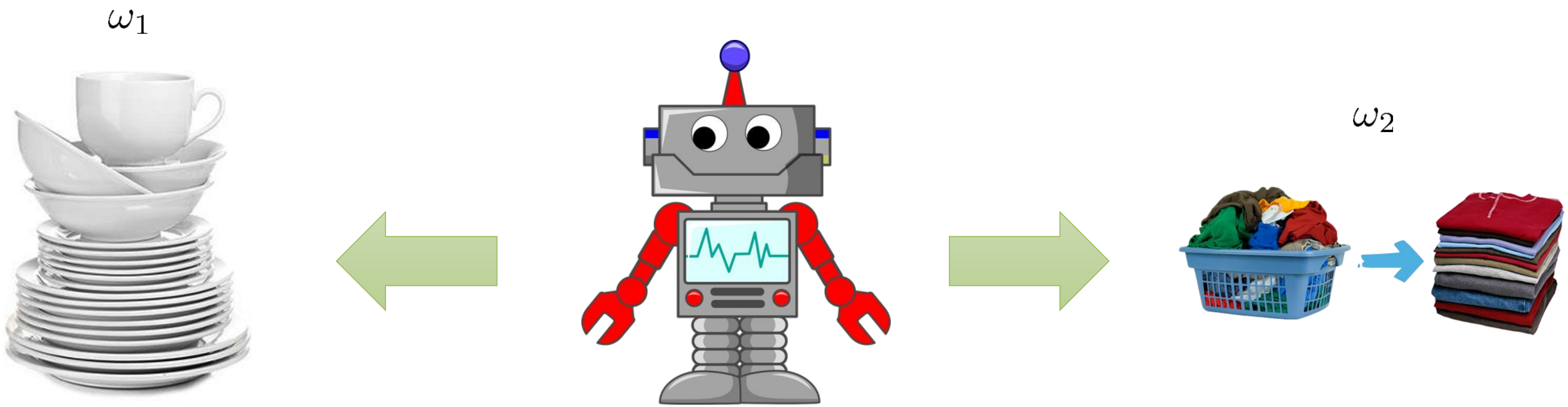
Distillation Transfer Results



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?

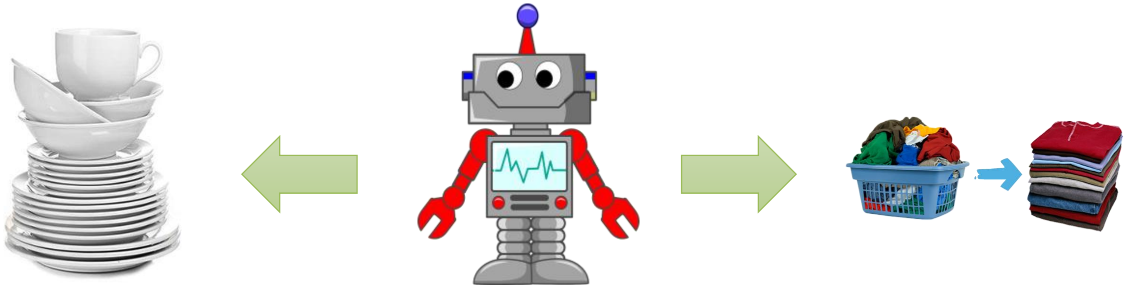


Contextual policies

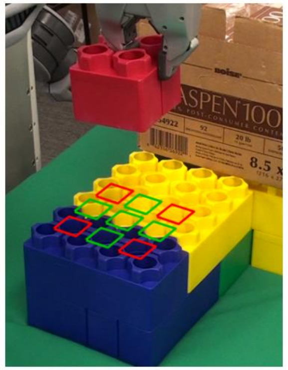
standard policy: $\pi_\theta(\mathbf{a}|\mathbf{s})$

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

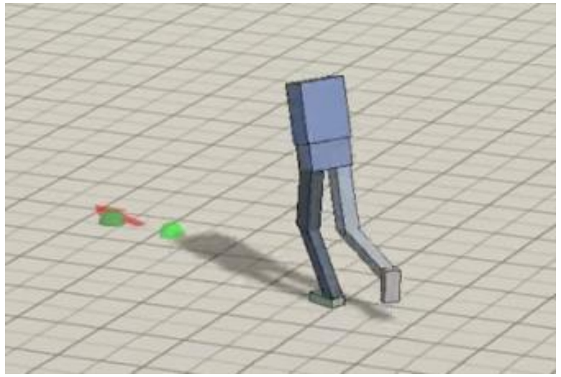
e.g., do dishes or laundry



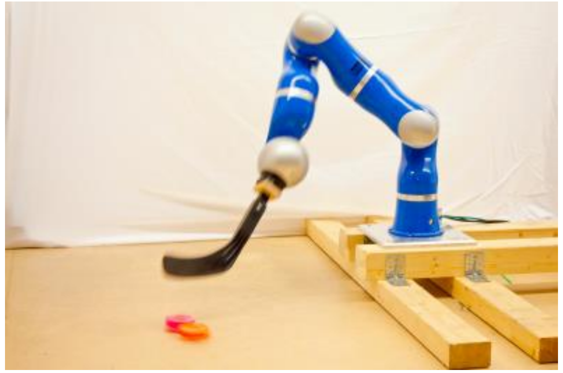
formally, simply defines augmented state space: $\tilde{\mathbf{s}} = \begin{bmatrix} \mathbf{s} \\ \omega \end{bmatrix}$ $\qquad \tilde{\mathcal{S}} = \mathcal{S} \times \Omega$



ω: stack location



ω: walking direction



ω: where to hit puck

images: Peng, van de Panne, Peters

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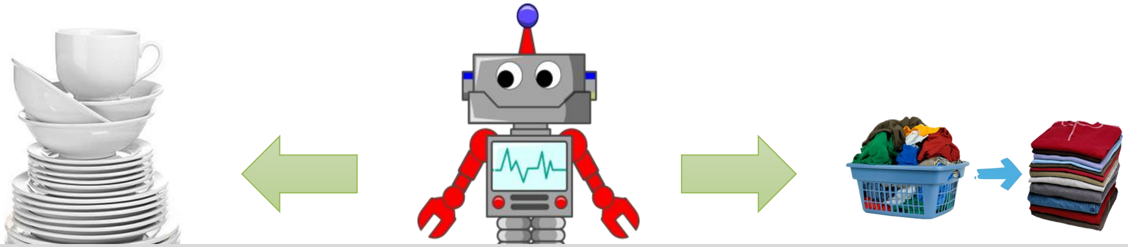

will discuss more in the context of meta-learning!

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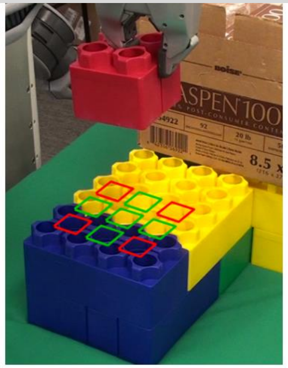

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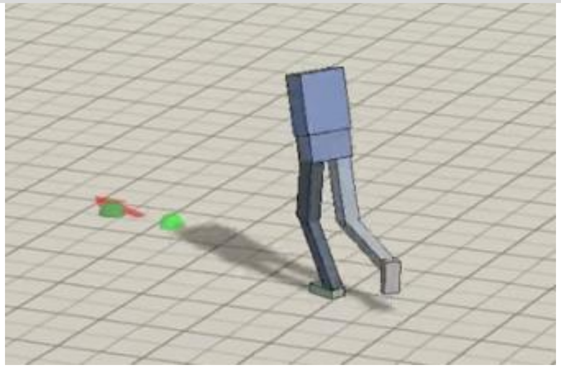


ω: walking direction

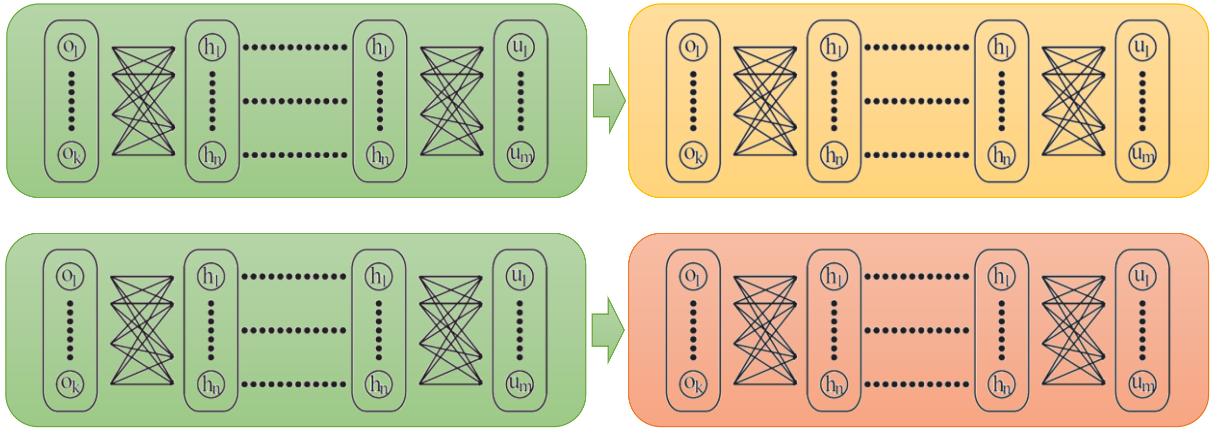
ω: where to hit puck

images: Peng, van de Panne, Peters

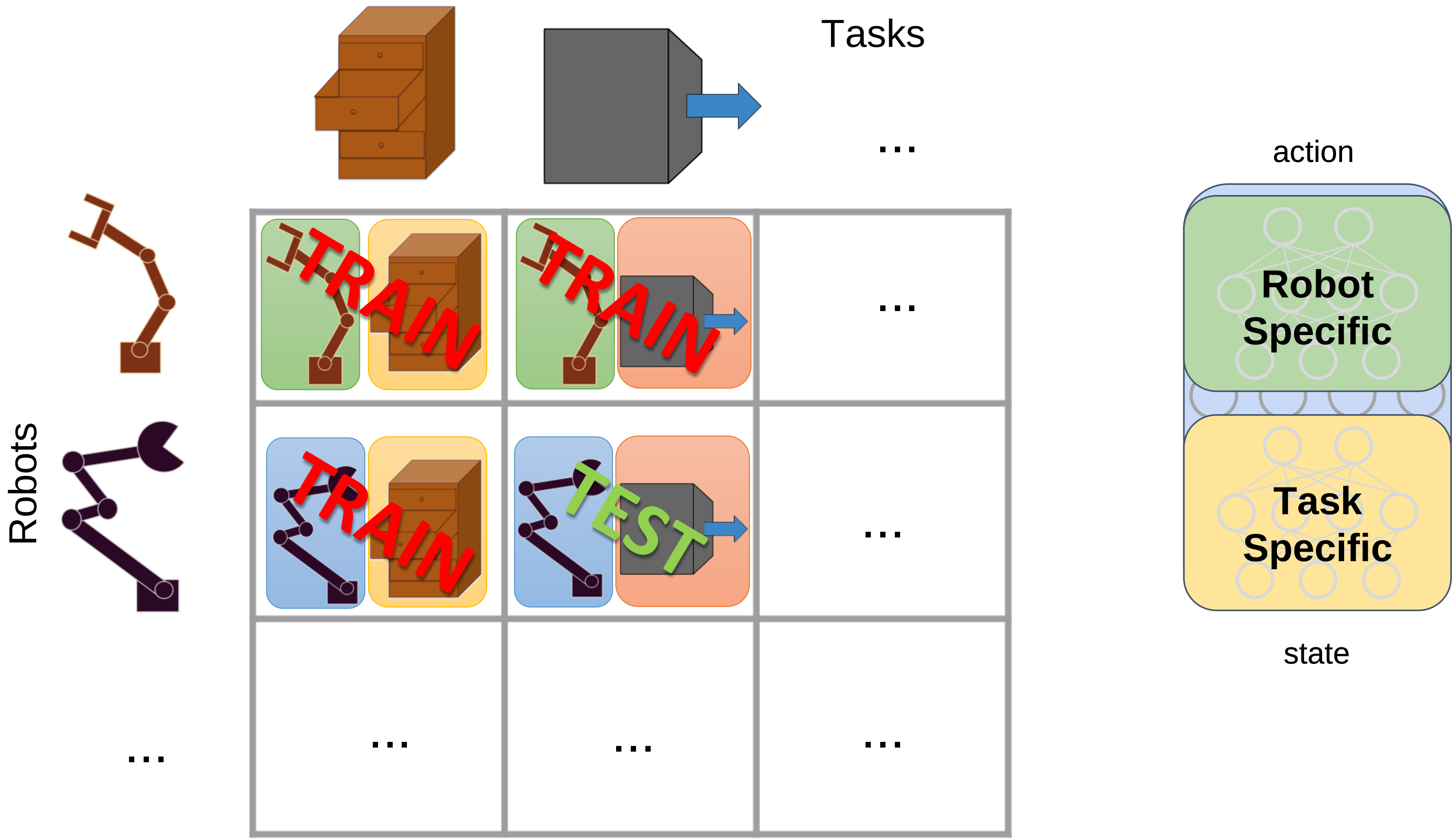
Architectures for multi-task transfer

- So far: single neural network for all tasks (in the end)
- What if tasks have some shared parts and some distinct parts?
  - Example: two cars, one with camera and one with LIDAR, driving in two different cities
  - Example: ten different robots trying to do ten different tasks
- Can we design architectures with *reusable components*?

Modular Policies

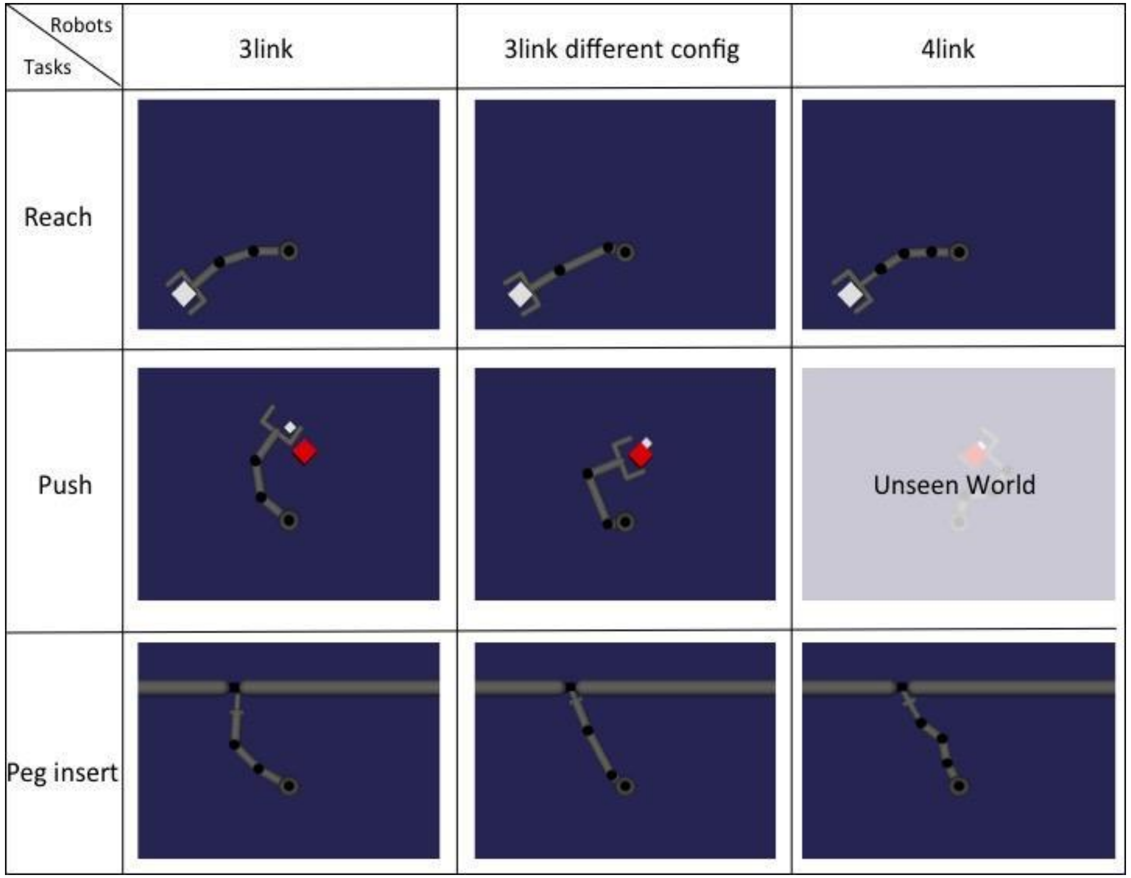


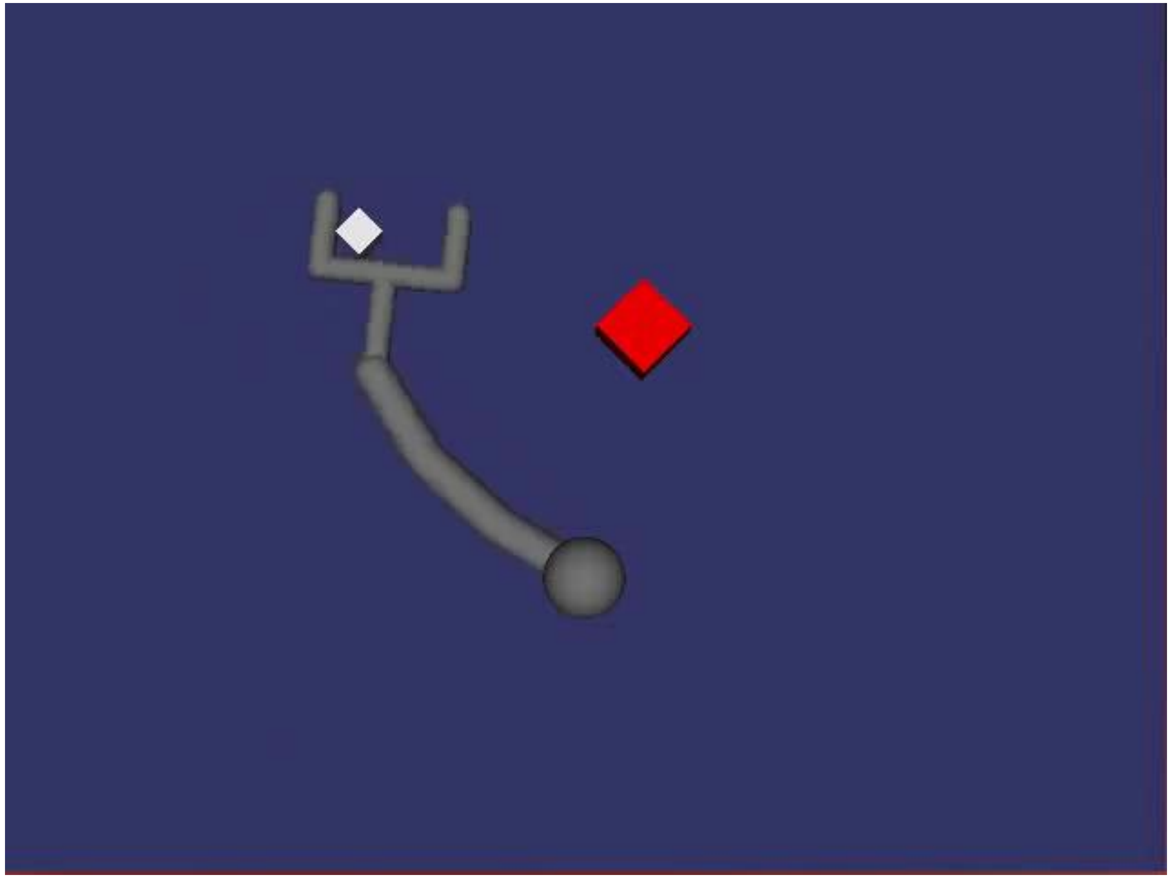
Modular networks



Devin*, Gupta*, et al. “Learning Modular Neural Network Policies…”

Modular networks





Multi-task learning summary

- More tasks = more diversity = better transfer
- Often easier to obtain multiple different but relevant prior tasks
- Model-based RL: transfer the physics, not the behavior
- Distillation: combine multiple policies into one, for concurrent multi-task learning (accelerate all tasks through sharing)
- Contextual policies: policies that are told *what* to do
- Architectures for multi-task learning: modular networks

Suggested readings

Fu, Levine, Abbeel. (2016). **One-Shot Learning of Manipulation Skills with Online Dynamics Adaptation and Neural Network Priors.**

Rusu et al. (2016). **Policy Distillation.**

Parisotto, Ba, Salakhutdinov. (2016). **Actor-Mimic: Deep Multitask and Transfer Reinforcement Learning.**

Devin*, Gupta*, Darrell, Abbeel, Levine. (2017). **Learning Modular Neural Network Policies for Multi-Task and Multi-Robot Transfer.**

How can we frame transfer learning problems?

1. “Forward” transfer: train on one task, transfer to a new task
   a) Just try it and hope for the best
   b) Finetu
   c) Archit
   d) Rando

more on this next time!

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