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

Unmodeled effects

Rajeswaran et al., “EPOpt: Learning robust neural network policies...”
Preparing for the unknown: explicit system ID

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”
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
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

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


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


Break
How can we frame transfer learning problems?

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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 if 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...”
Fu et al., “One-Shot Learning of Manipulation Skills with Online Dynamics Adaptation...”
Fu et al., “One-Shot Learning of Manipulation Skills with Online Dynamics Adaptation...”
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
Goal: learn a single policy that can play all Atari games

**POLICY DISTILLATION**

**ACTOR-MIMIC**
**DEEP MULTITASK AND TRANSFER REINFORCEMENT LEARNING**

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

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

Slide adapted from C. Finn
**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

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

**Intuition:** more knowledge in soft targets than hard labels!

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Slide adapted from G. Hinton, see also Hinton et al. “Distilling the Knowledge in a Neural Network”
Distillation for Multi-Task Transfer

\[ \mathcal{L} = \sum_a \pi_{E_i}(a|s) \log \pi_{AMN}(a|s) \]

(just supervised learning/distillation)

analogous to guided policy search, but for transfer learning

\rightarrow \text{see model-based RL slides}

some other details
(e.g., feature regression objective)
– see paper

Distillation Transfer Results

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: \( \pi_\theta(a|s) \)

contextual policy: \( \pi_\theta(a|s, \omega) \)

\( \omega \): stack location
\( \omega \): walking direction
\( \omega \): where to hit puck

e.g., do dishes or laundry

formally, simply defines augmented state space:

\[
\tilde{s} = \begin{bmatrix} s \\ \omega \end{bmatrix}
\]

\( \tilde{S} = S \times \Omega \)
Contextual policies

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

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

will discuss more in the context of meta-learning!

$\omega$: stack location

$\omega$: walking direction

$\omega$: where to hit puck
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

<table>
<thead>
<tr>
<th>Robots</th>
<th>Tasks</th>
<th>3link</th>
<th>3link different config</th>
<th>4link</th>
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<td><img src="image2" alt="Reach 3link different config" /></td>
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<td><img src="image4" alt="Push 3link" /></td>
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<td><img src="image8" alt="Peg insert 3link different config" /></td>
<td><img src="image9" alt="Peg insert 4link" /></td>
</tr>
</tbody>
</table>
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.


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more on this next time!