

Transfer and Meta Learning

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 - Imitation Learning
 - Inverse Reinforcement Learning
- Today:

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 - How do we **transfer** knowledge from one domain to another?
(e.g. simulated to real-world)

Transfer and Meta Learning

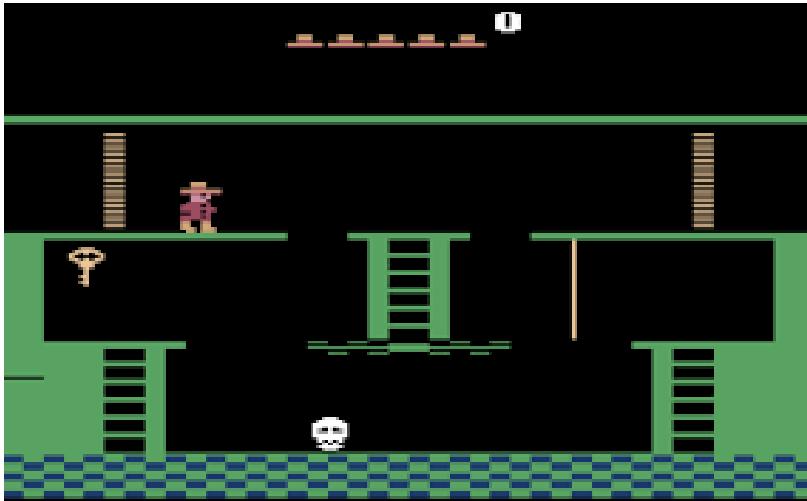
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 - Imitation Learning
 - Inverse Reinforcement Learning
- Today:
 - How do we **transfer** knowledge from one domain to another?
(e.g. simulated to real-world)
 - How do we learn how to learn? (**Meta** learning)

Transfer Learning and Montezuma's Revenge

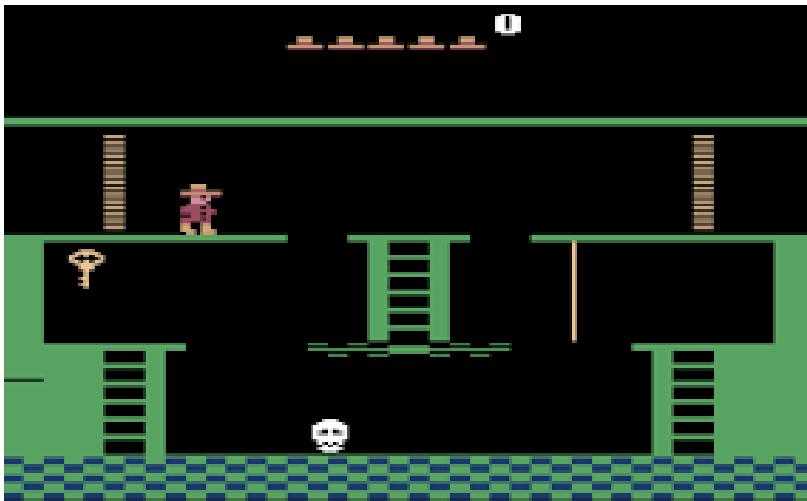
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Could an RL agent be better at Montezuma's revenge after watching Indiana Jones?

Transfer Learning

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In RL, task=MDP

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Source domain → target domain

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In RL, task=MDP

Source domain → target domain

- "shot" = number of attempts in the target domain
- "0-shot" = run policy in target domain
- "1-shot" = try task once
- "few shot"

Transfer Learning

How should prior knowledge be stored?

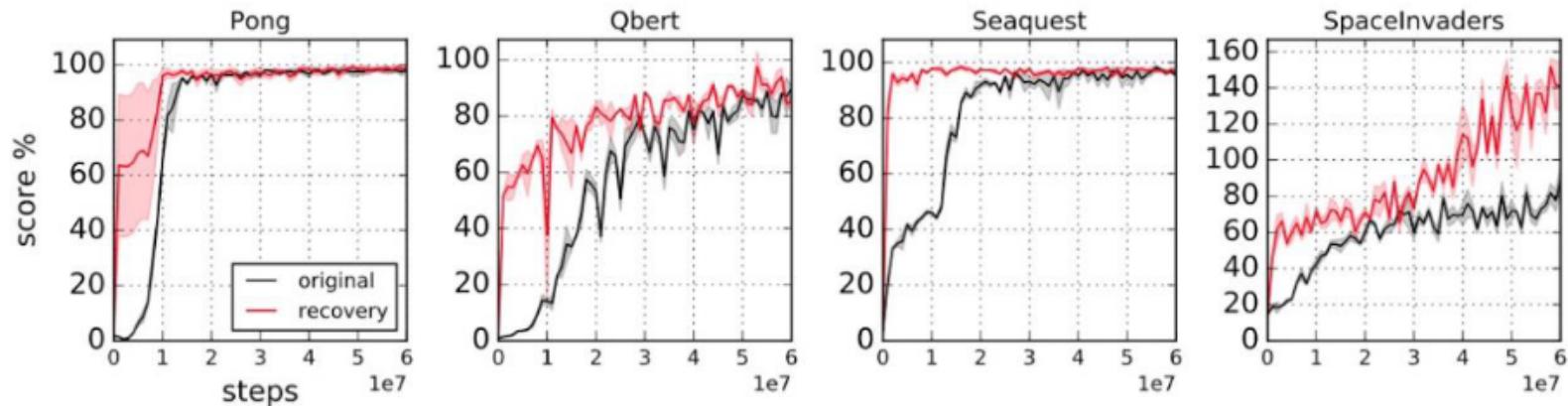
- Q-function
- Policy
- Model
- Features¹/hidden states

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Representation Bottleneck



Transfer Learning

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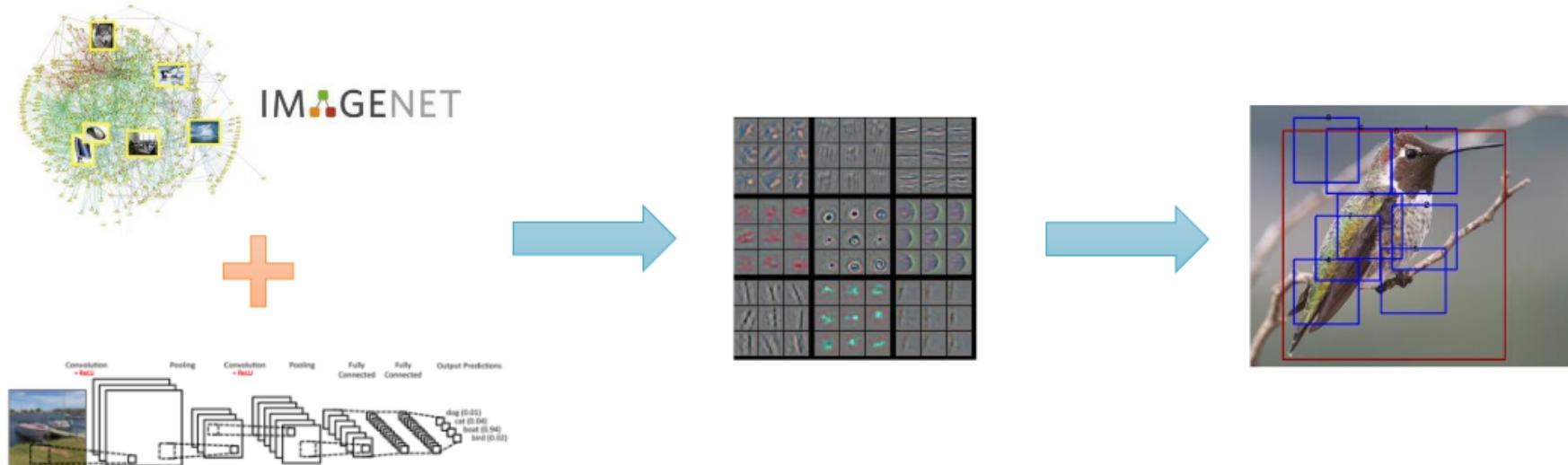
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Pretraining + Finetuning



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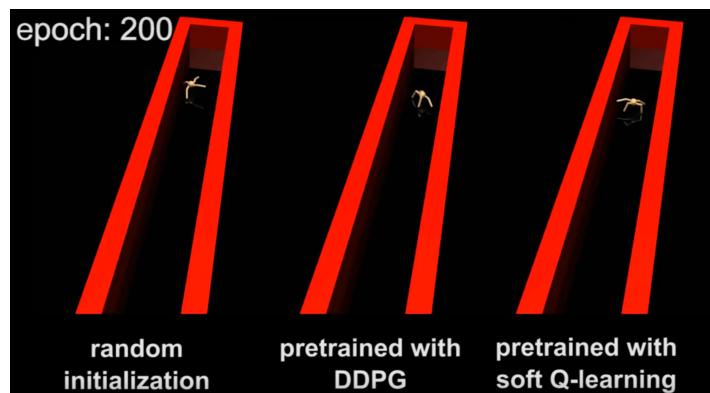


Pretrain: reward speed in any direction

Pretraining + Finetuning



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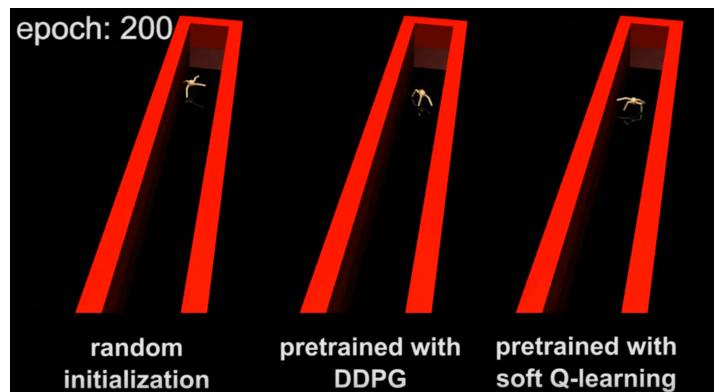


Fine Tune: reward speed in specific direction

Pretraining + Finetuning



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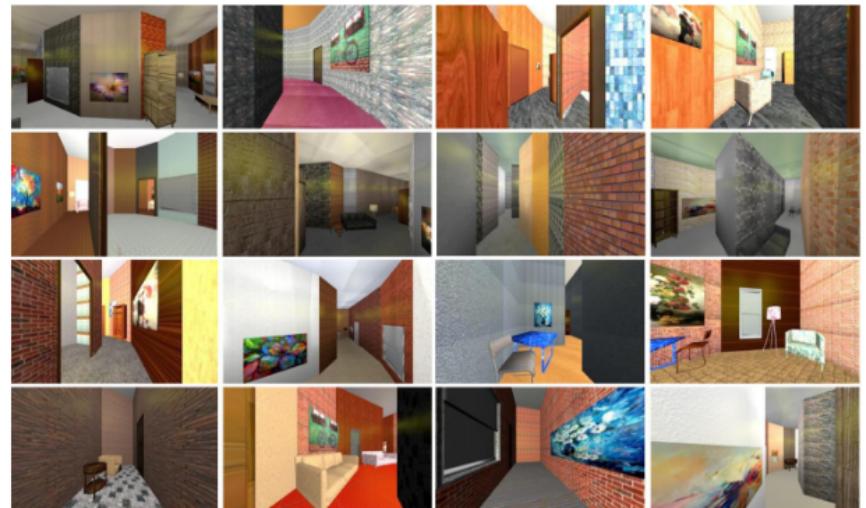


Fine Tune: reward speed in specific direction

$$\pi(a|s) \propto_a \exp(Q(s, a))$$

<https://sites.google.com/view/softqlearning/home>

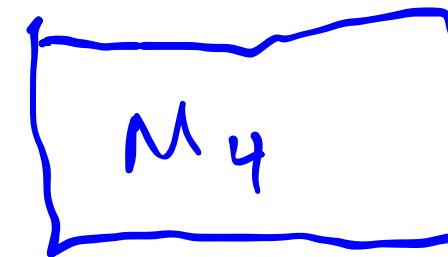
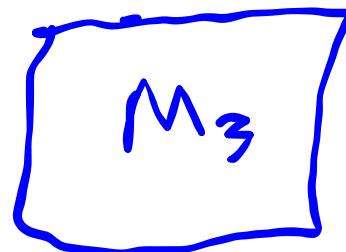
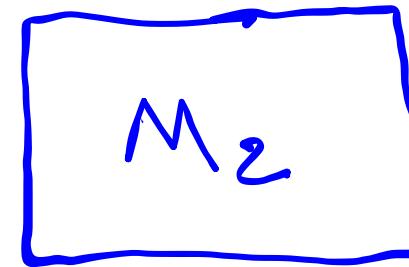
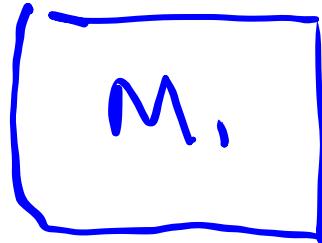
CAD2RL



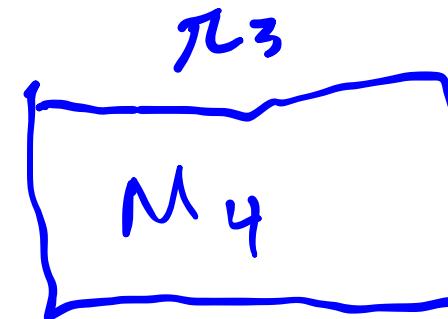
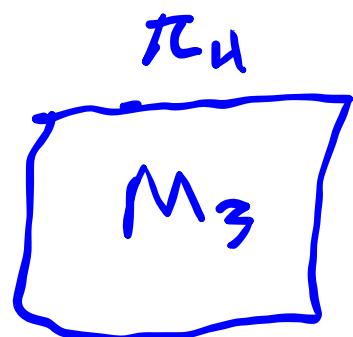
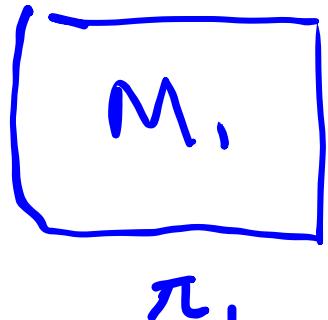
Key: Diversity

Actor Mimic

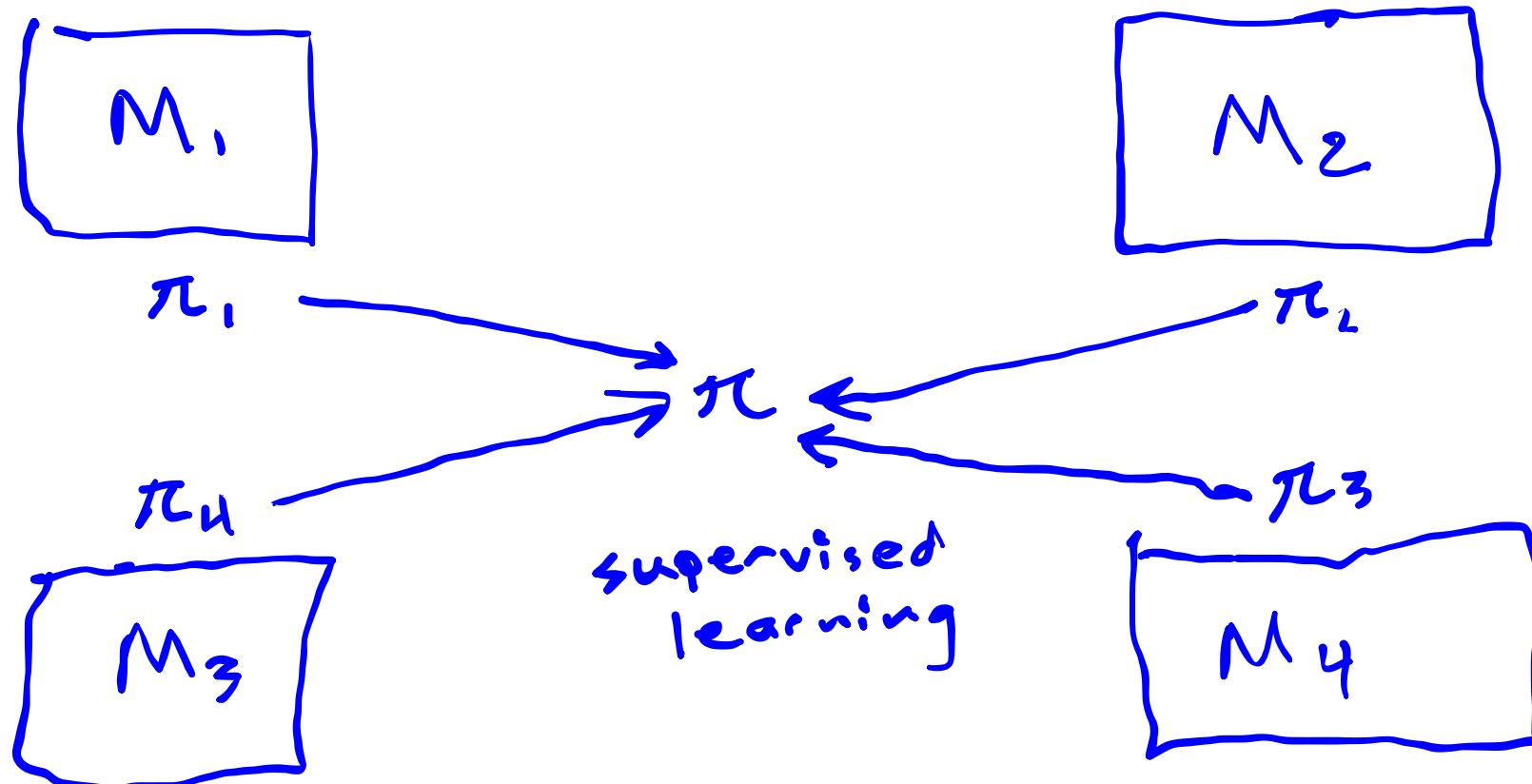
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- Keep a family of good policies and associated successor features with a variety of weights.

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- Keep a family of good policies and associated successor features with a variety of weights.
- In target domain, start with best policy from this set and finetune/plan online

Meta Learning: Motivation

https://www.youtube.com/watch?v=1eYqV_vGJY

Meta Learning

Problem formulation: