Transfer and Meta Learning

- **Last time:**
  - Imitation Learning
  - Inverse Reinforcement Learning
- **Today:**

(Lecture content from Sergey Levine's CS 285 at Berkeley)

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

(Lecture content from Sergey Levine's CS 285 at Berkeley)

Transfer and Meta Learning

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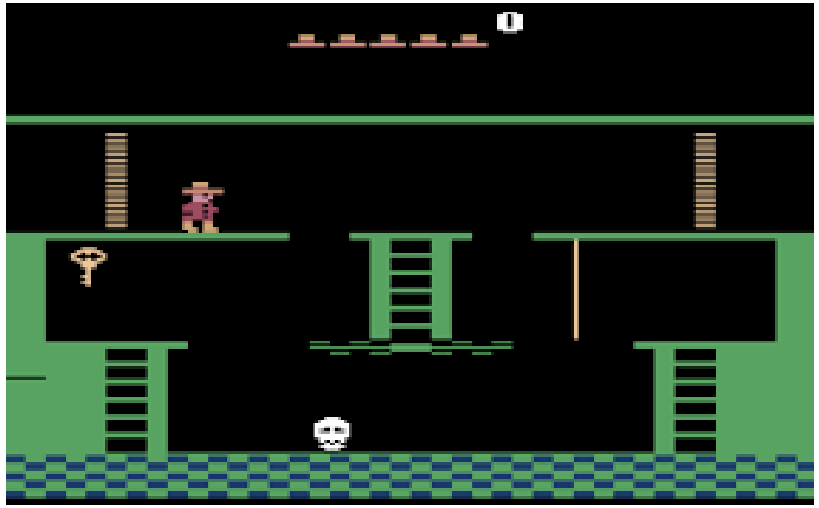
  - Imitation Learning
  - Inverse Reinforcement Learning
- **Today:**
  - How do we **transfer** knowledge from one domain to another? (e.g. simulated to real-world)
  - How do we learn how to learn? (**Meta** learning)

(Lecture content from Sergey Levine's CS 285 at Berkeley)

Transfer Learning and Montezuma's Revenge

Transfer Learning and Montezuma's Revenge



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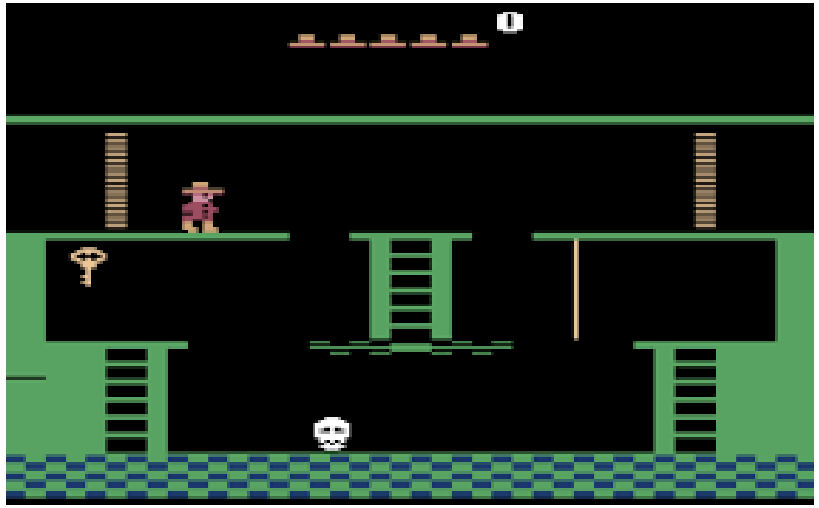

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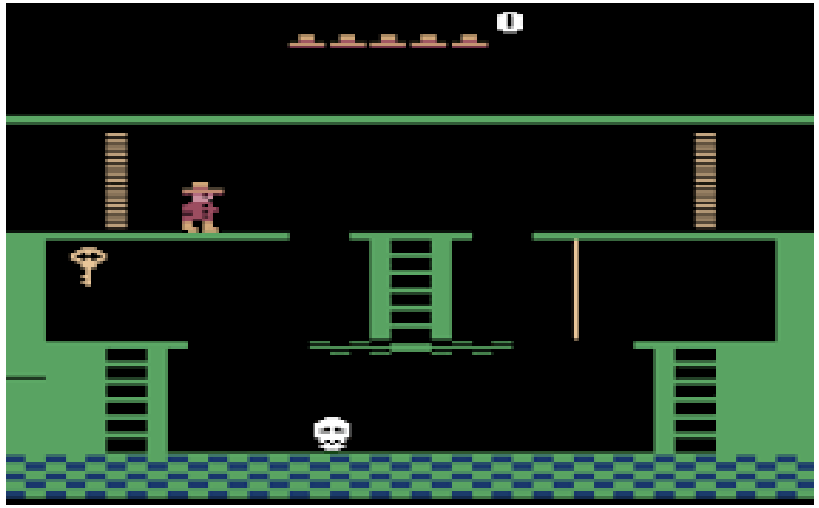

Could an RL agent be better at Montezuma's revenge after watching Indiana Jones?

Transfer Learning

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Transfer Learning: Use experience from one set of tasks for faster learning and better performance on a new task

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In RL, task=MDP

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Source domain $\rightarrow$ target domain

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In RL, task=MDP

Source domain $\rightarrow$ 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
- Features/hidden states

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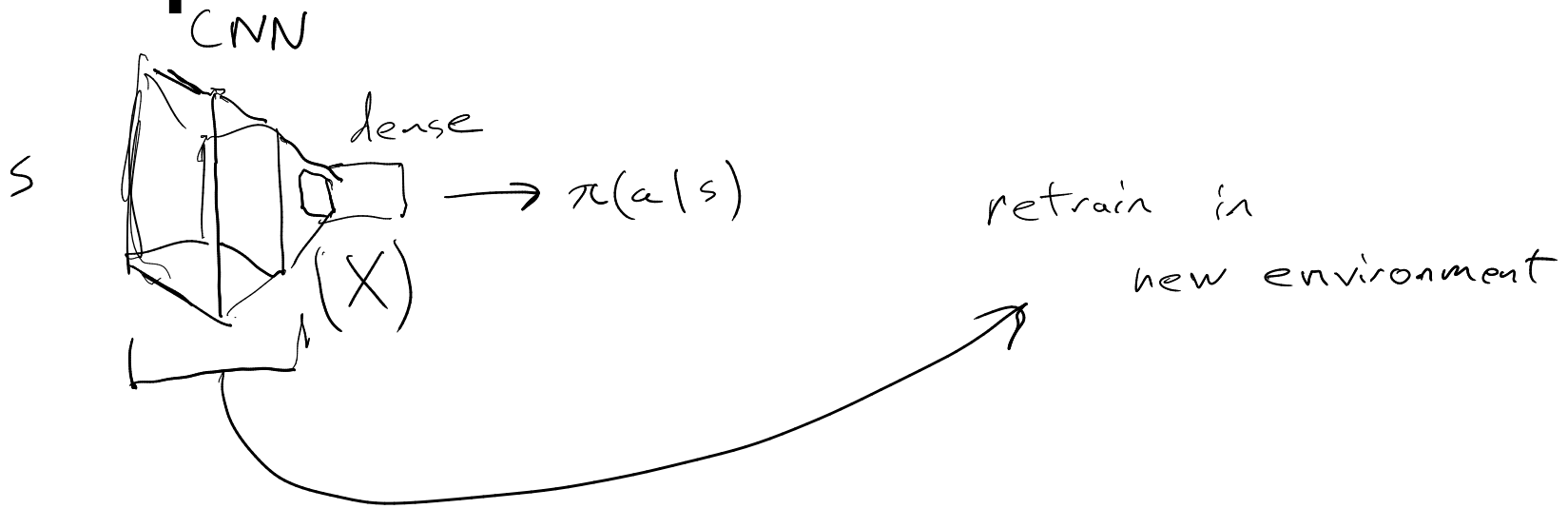
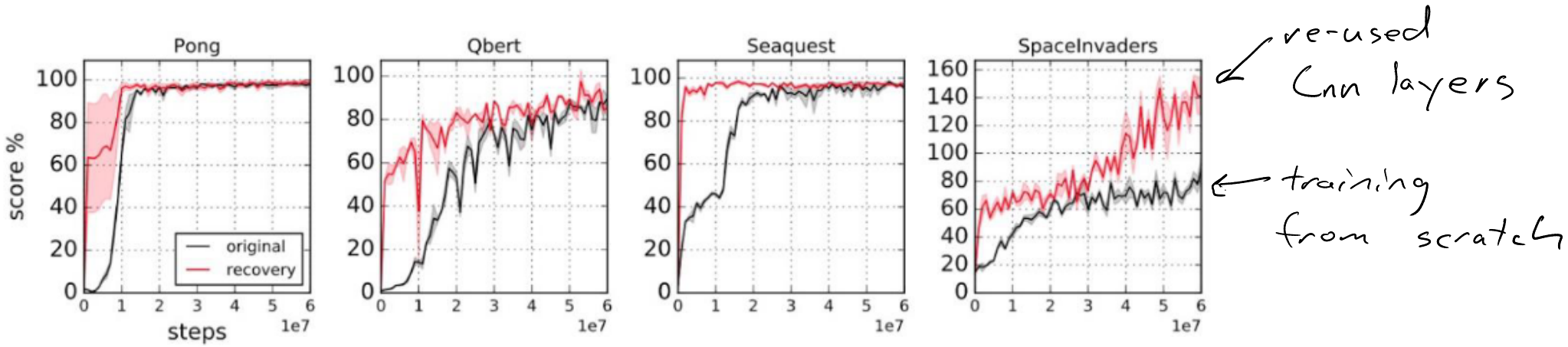
Representation Bottleneck





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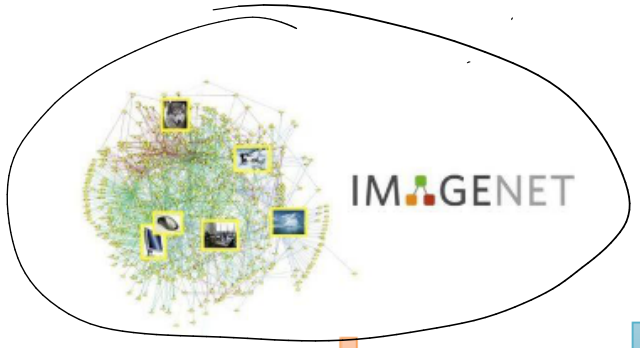
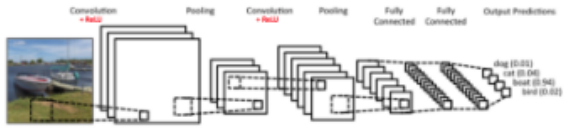
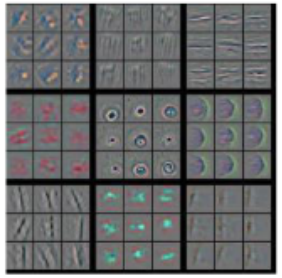
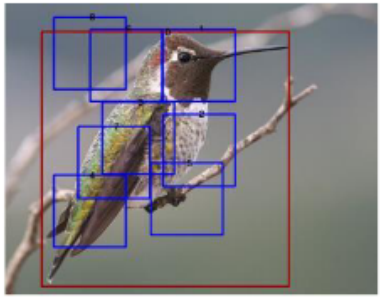
Pretraining + Finetuning









Hummingbird / Not hummingbird

Pretraining + Finetuning

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Pretrain: reward speed in any direction

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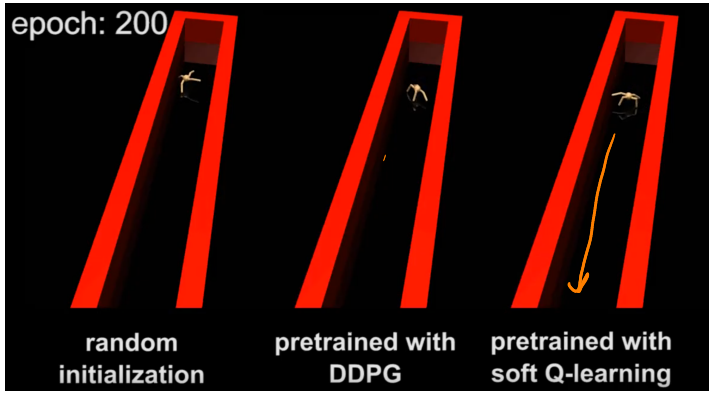
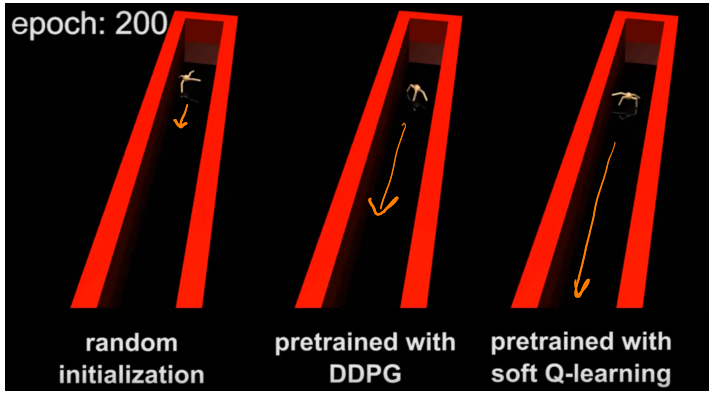


Fine Tune: reward speed in specific direction

Pretraining + Finetuning

Pretrain: reward speed in any direction



Fine Tune: reward speed in specific direction

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

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

CAD2RL

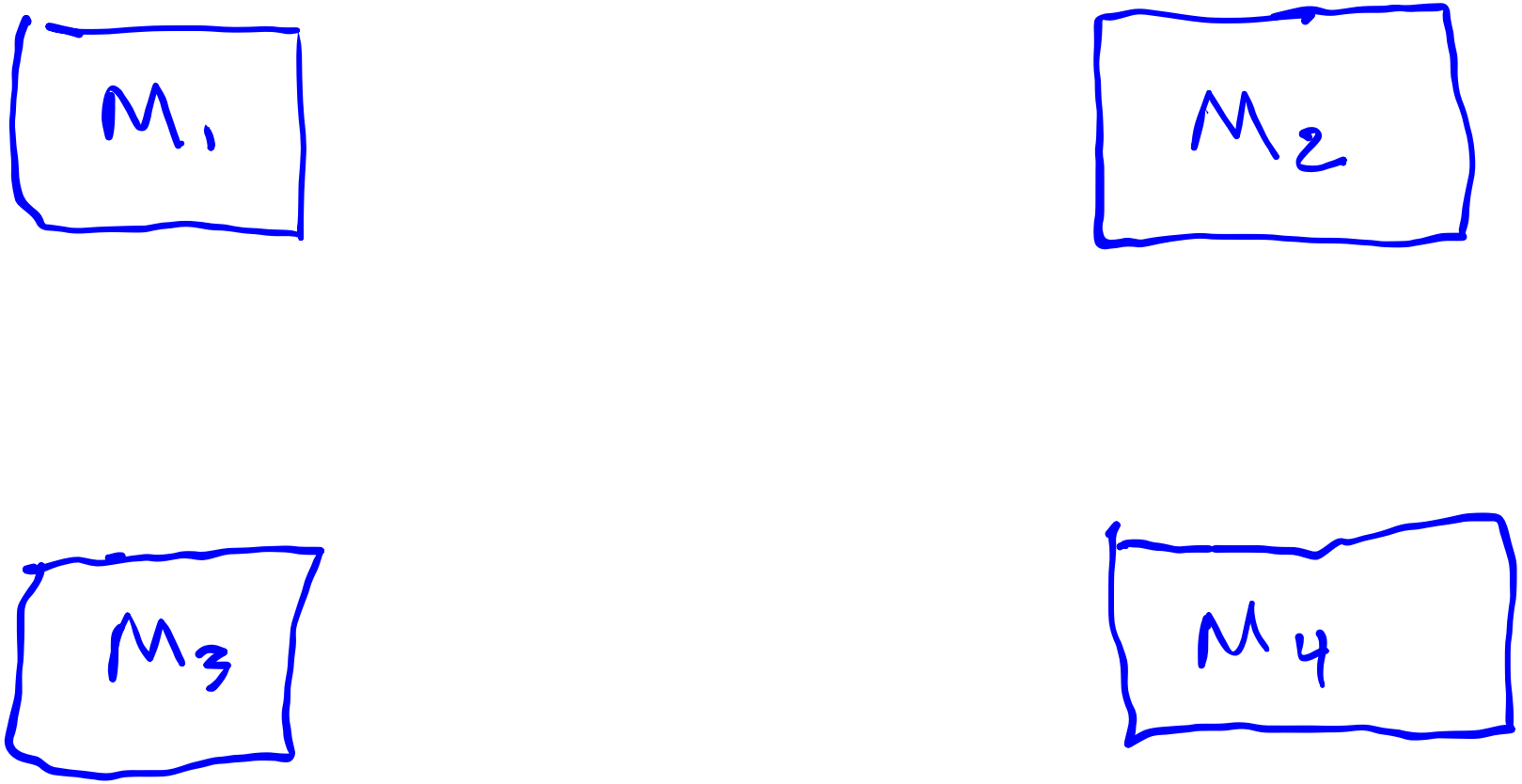
navigated in real world

trained

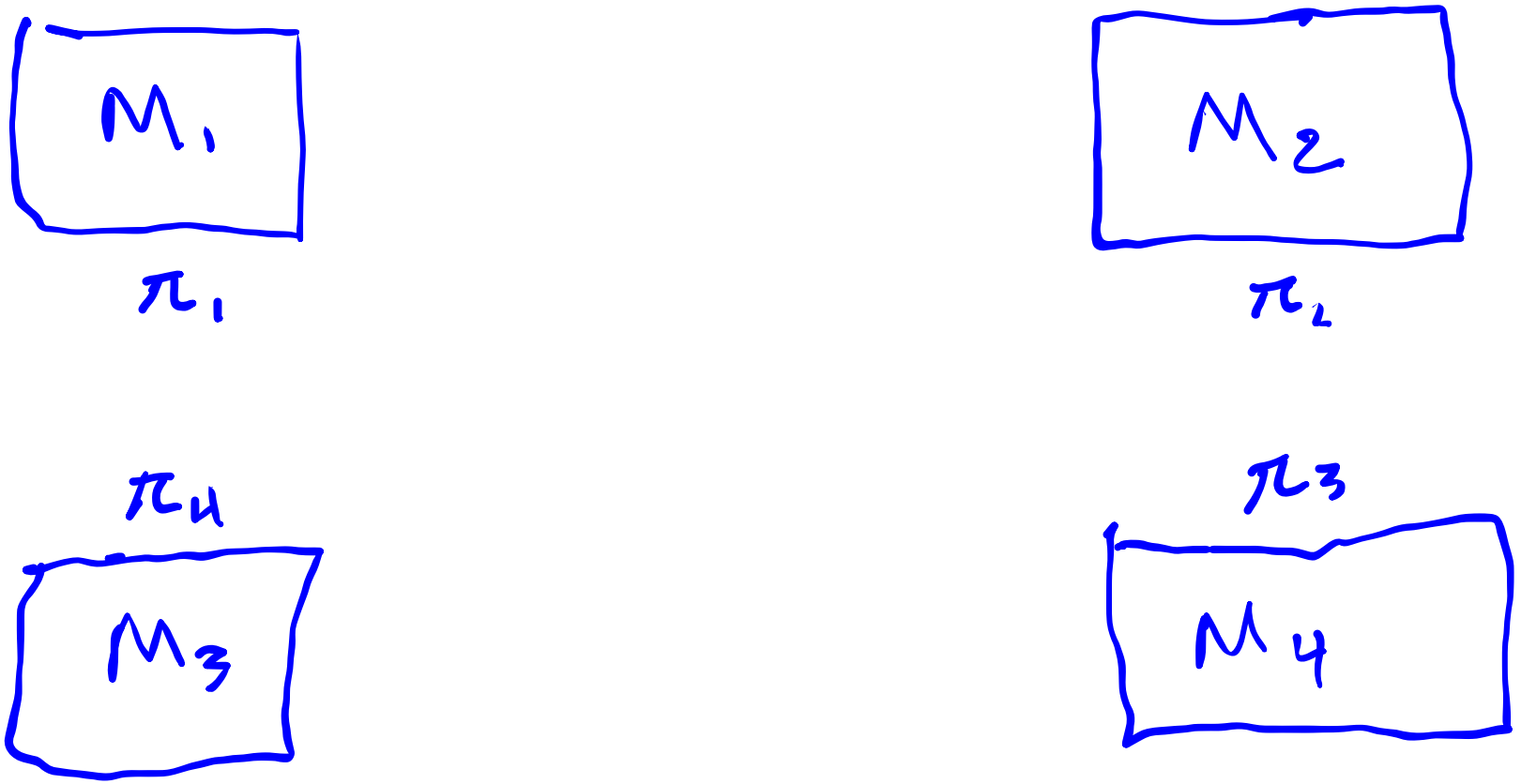
Key: Diversity

Actor Mimic

Actor Mimic



Actor Mimic



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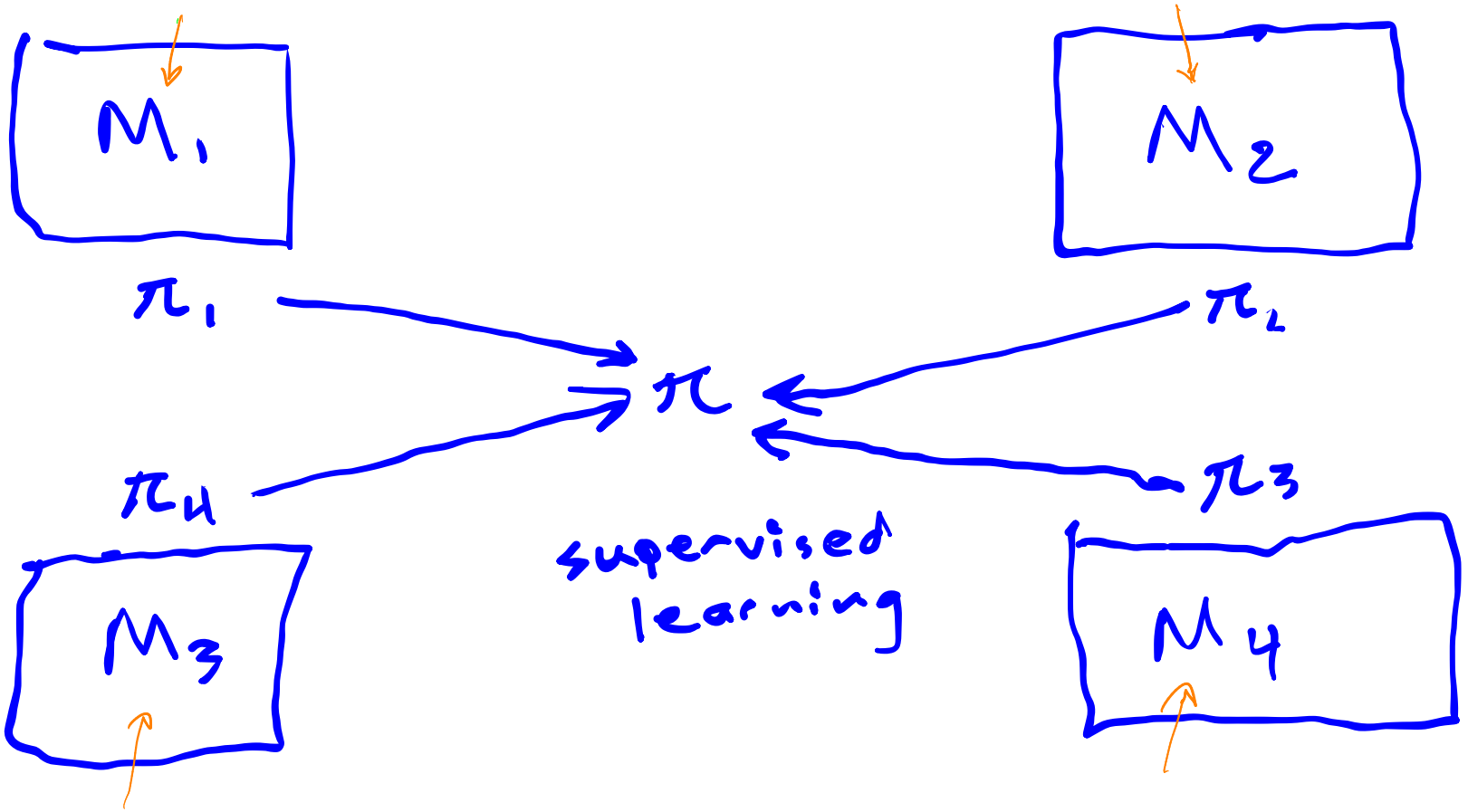

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Successor Features

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- All domains have same S, A, T, γ
- Difference: R

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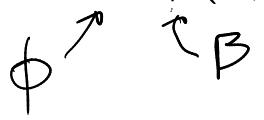
All domains have same S, A, T, γ

Difference: R

Let $R(s,a) = w^\top \phi(s,a)$ where ϕ is a feature vector.



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Important: Does this yield optimal policy for R'?

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How to use this in practice:

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

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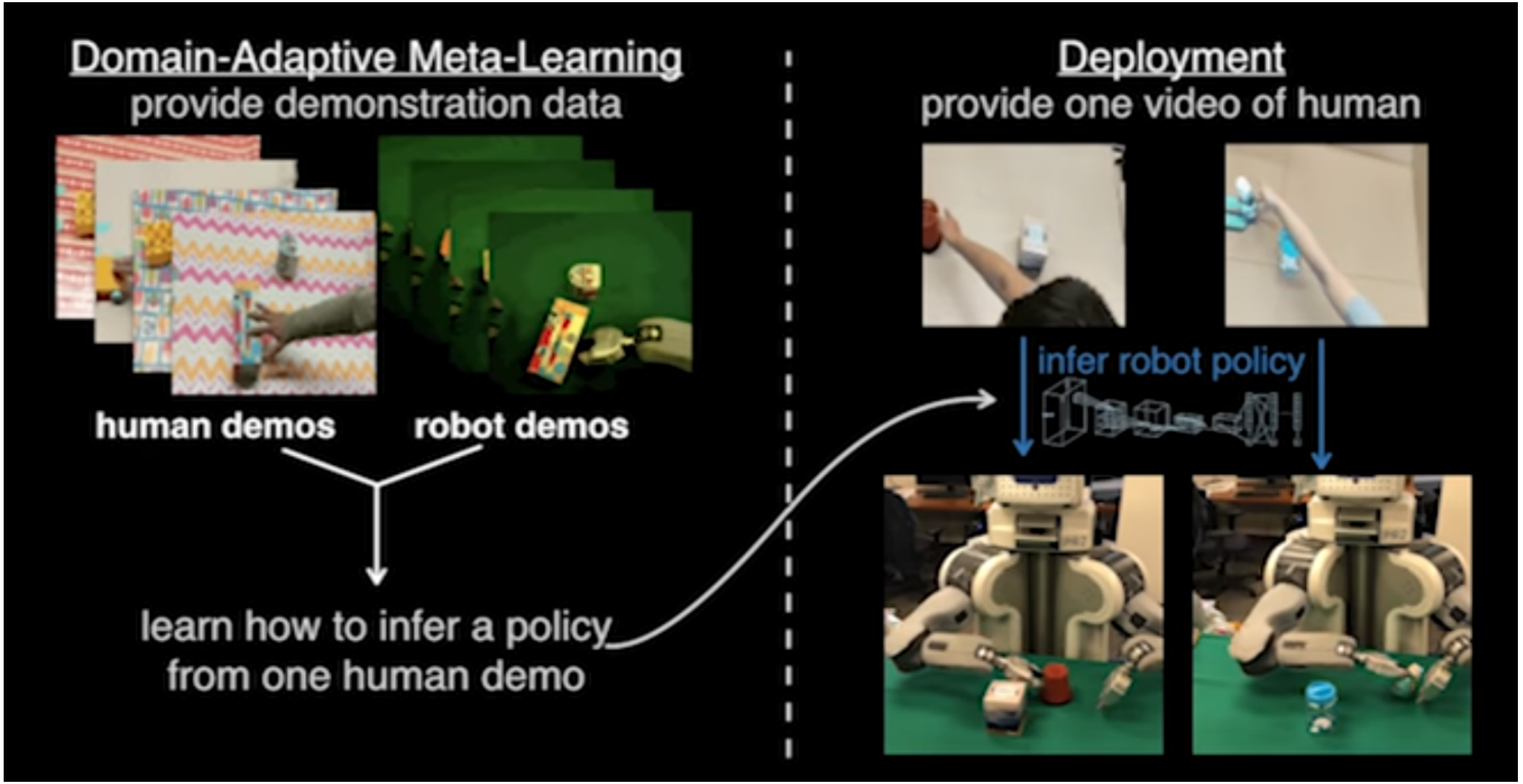
How to use this in practice:

- 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



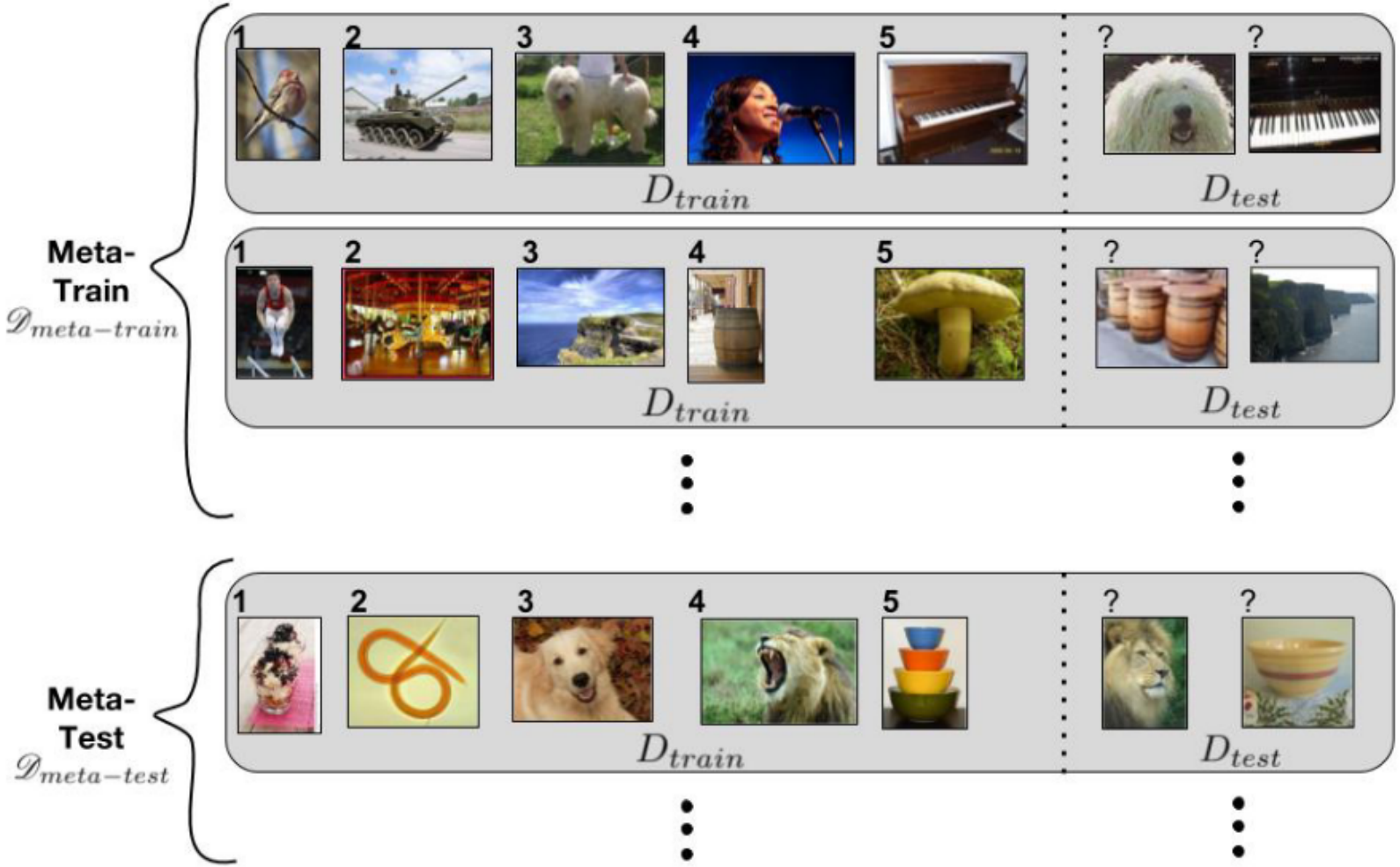
https://www.youtube.com/watch?v=1eYqV_vGIJY

Meta Learning

Meta Learning

Machine Learning Data Set

Meta Learning



Meta Reinforcement Learning

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RL

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RL

$$\theta^* = \underset{\theta}{\operatorname{argmax}} \, \mathrm{E}_{\pi_\theta} [R(\tau)]$$

Meta Reinforcement Learning

RL

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$$= f_{\mathrm{RL}}(M)$$

Meta Reinforcement Learning

RL **Meta RL**

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Meta RL

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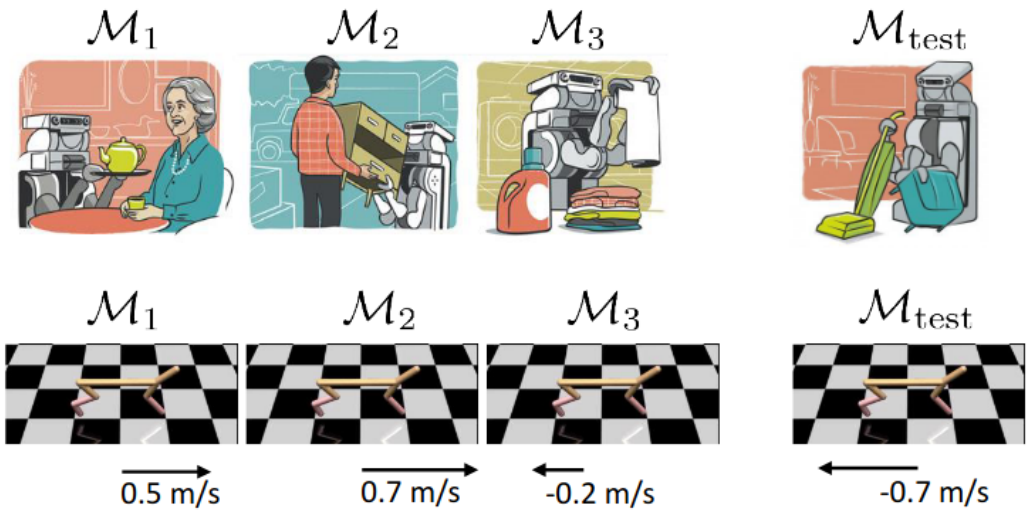

Image: Sergey Levine CS285 slides

Meta Reinforcement Learning

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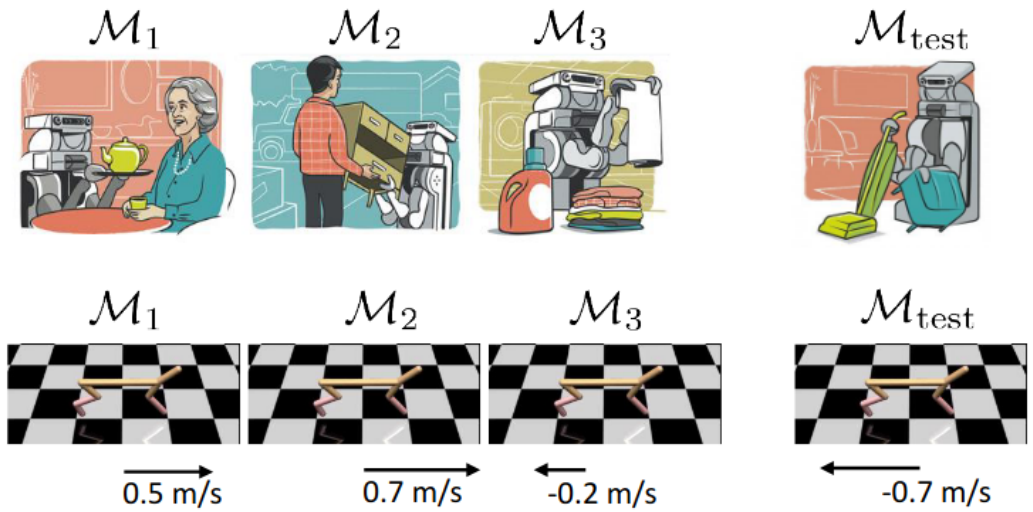

Image: Sergey Levine CS285 slides

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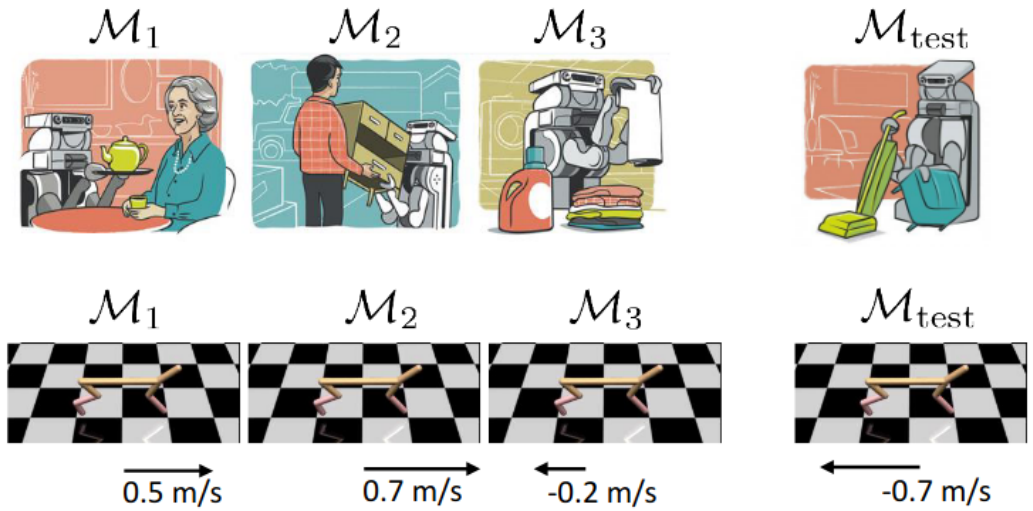

Image: Sergey Levine CS285 slides

Important: Exploration can speed up Meta RL

Meta Reinforcement Learning

Approach 1: Pose as POMDP

Meta Reinforcement Learning

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$$S = S_M \times \{1, \ldots, n\} \qquad s = (s_M, i)$$

Meta Reinforcement Learning

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Meta Reinforcement Learning

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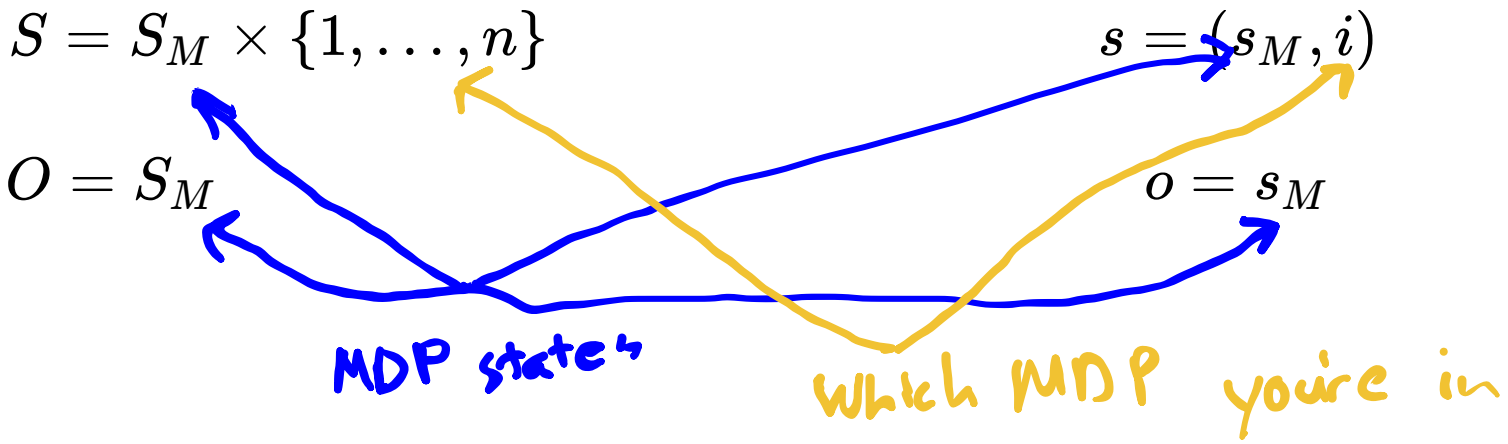

Meta Reinforcement Learning

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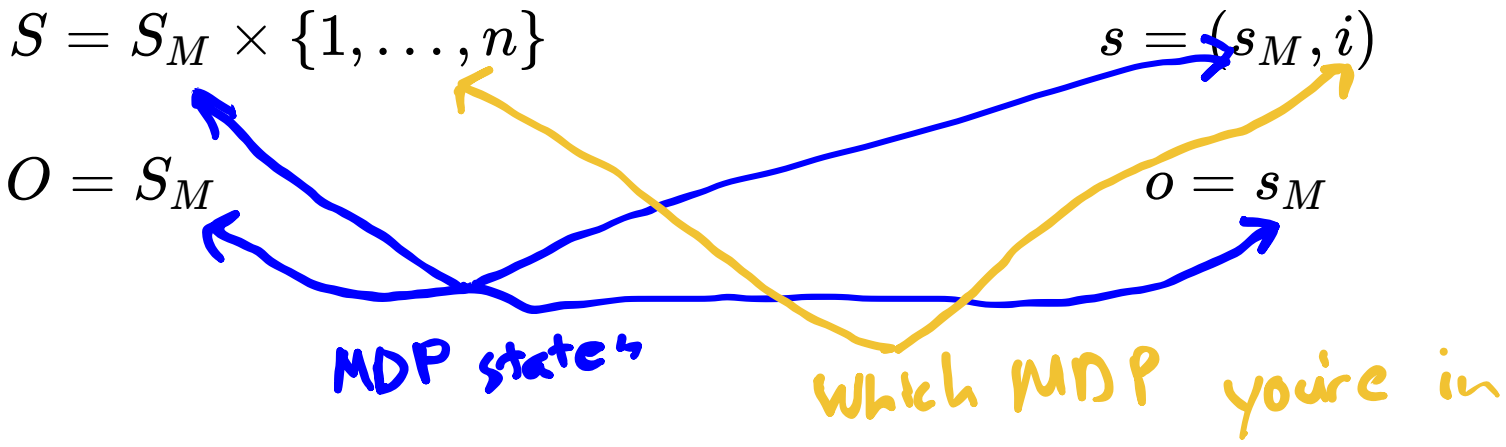

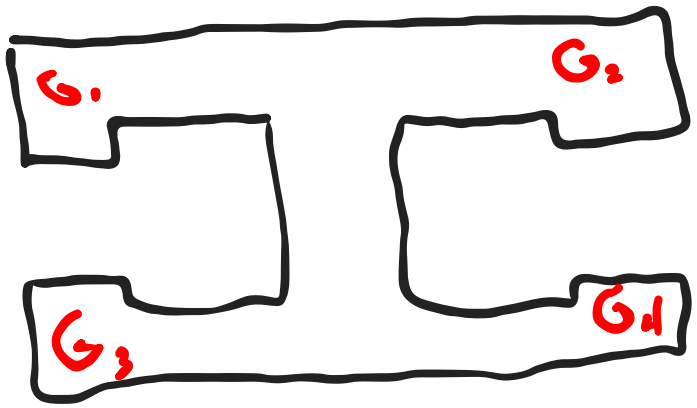

Meta Reinforcement Learning

Meta Reinforcement Learning

Approach 2: Gradient-Based Meta-RL (MAML)

Meta Reinforcement Learning

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RL: Policy Gradient

Meta Reinforcement Learning

Approach 2: Gradient-Based Meta-RL (MAML)

RL: Policy Gradient

$$\theta^{k+1} \leftarrow \theta^k + \alpha \nabla_\theta J(\theta^k)$$

Meta Reinforcement Learning

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Meta Reinforcement Learning

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Meta Policy Gradient

Meta Reinforcement Learning

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Model Agnostic Meta Learning (MAML) for RL

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Meta Policy Gradient

$$\theta \leftarrow \theta + \beta \sum_i \nabla_\theta J_i[\theta + \alpha \nabla_\theta J_i(\theta)]$$

Meta Reinforcement Learning

Approach 2: Gradient-Based Meta-RL (MAML)

RL: Policy Gradient

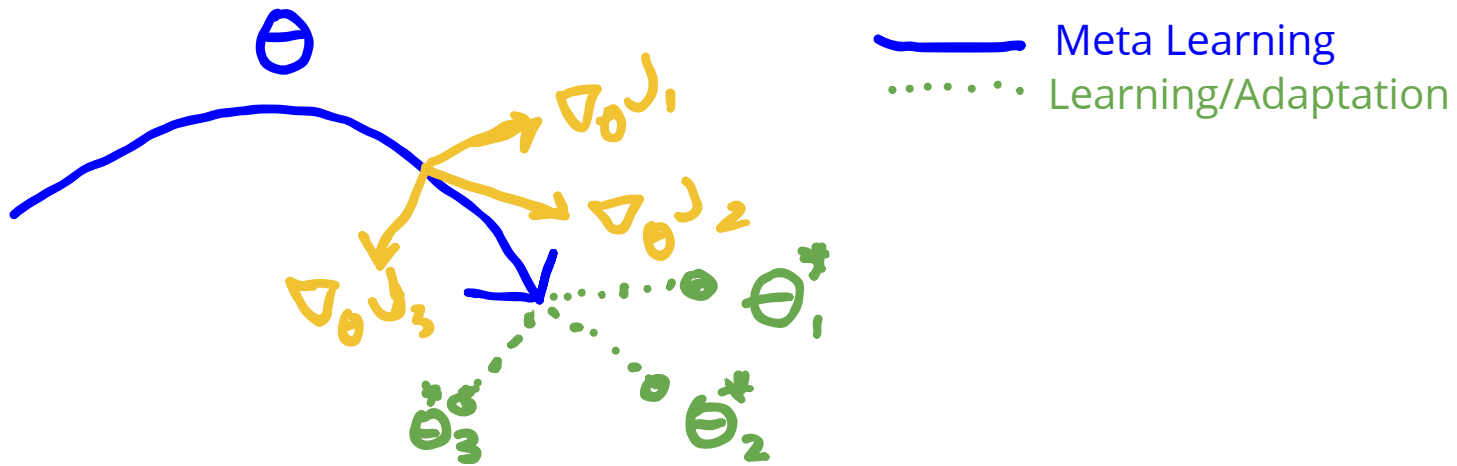
$$\theta^{k+1} \leftarrow \theta^k + \alpha \nabla_\theta J(\theta^k)$$

Model Agnostic Meta Learning (MAML) for RL

$$f_\theta(M_i) = \theta + \alpha \nabla_\theta J_i(\theta)$$

Meta Policy Gradient

$$\theta \leftarrow \theta + \beta \sum_i \nabla_\theta J_i[\theta + \alpha \nabla_\theta J_i(\theta)]$$



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- Various methods exist to transfer via knowledge stored in the **policy**, **model**, **value function**, or **other features**.
- In **Meta Learning**, the goal is to learn how to master a new environment quickly.
- A meta learning problem can be posed as a **POMDP**.
- In model agnostic meta learning (**MAML**), the policy is parameterized so that **one gradient step** in the new environment will produce a good policy.