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

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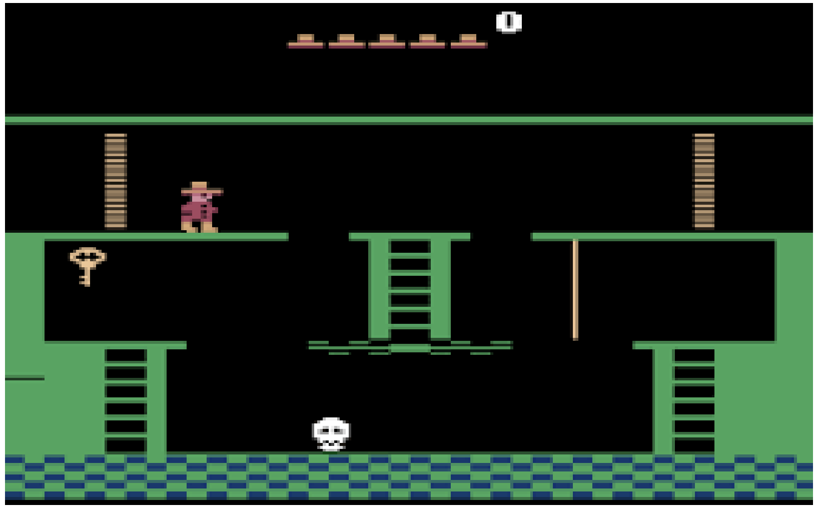

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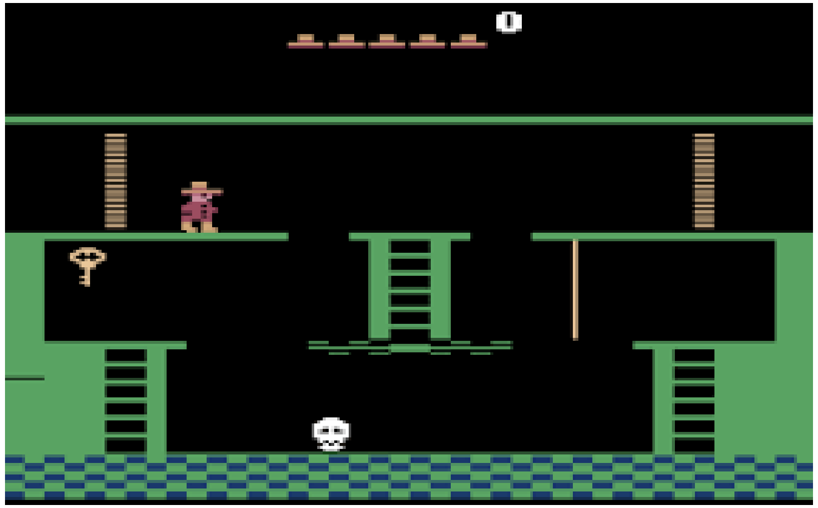

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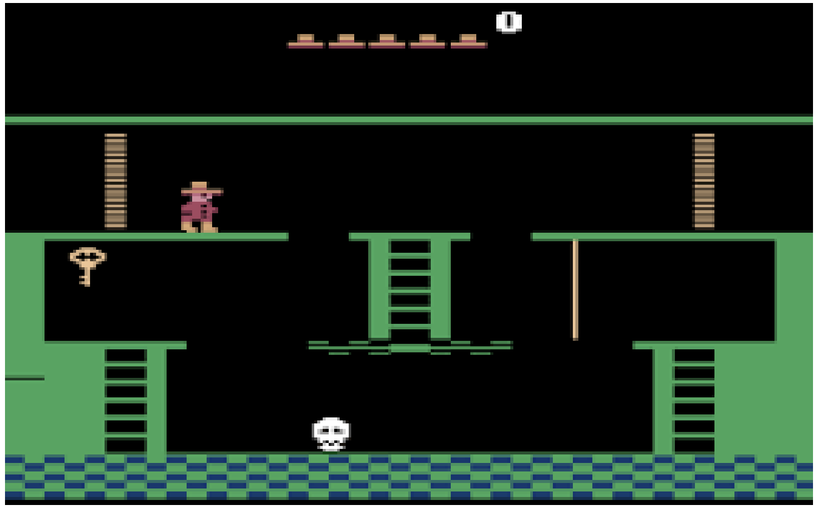

Could an RL agent be better at Montezuma's revenge after watching Indiana Jones?

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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
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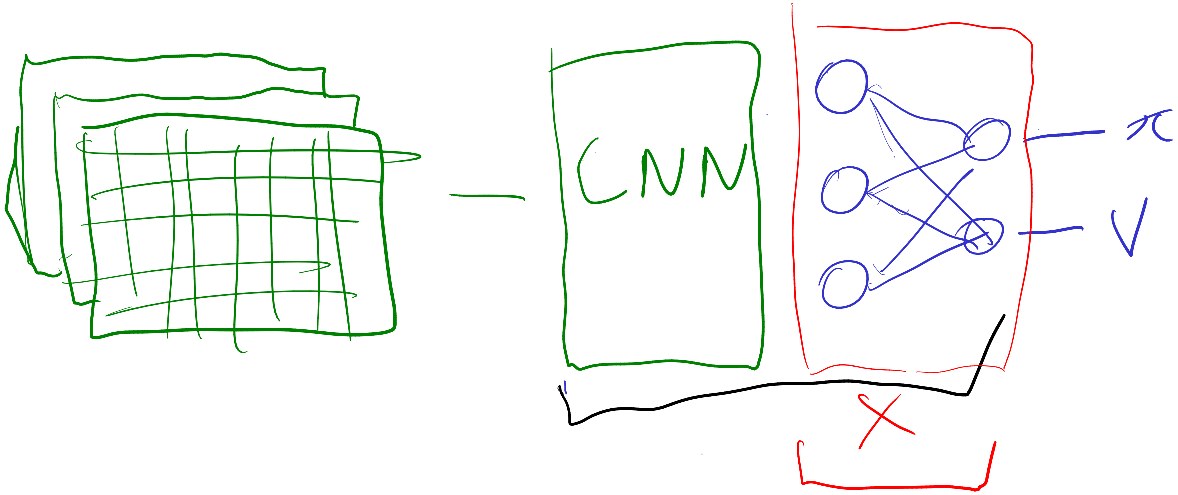
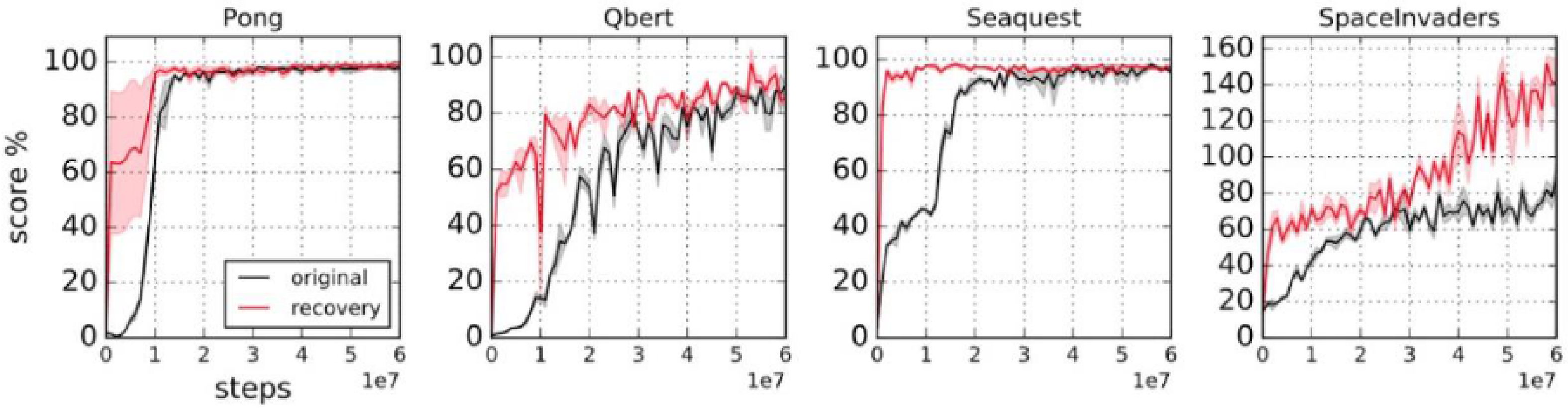
Representation Bottleneck





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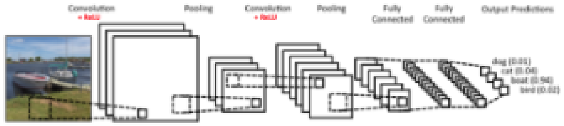
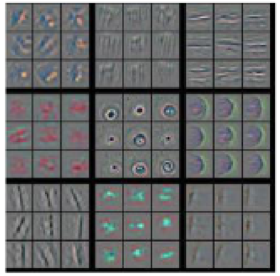
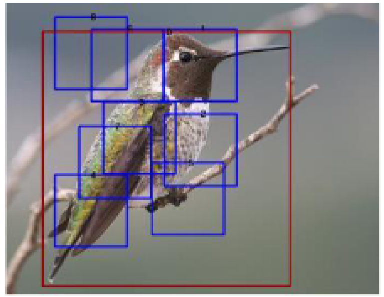
Pretraining + Finetuning







Pretraining + Finetuning

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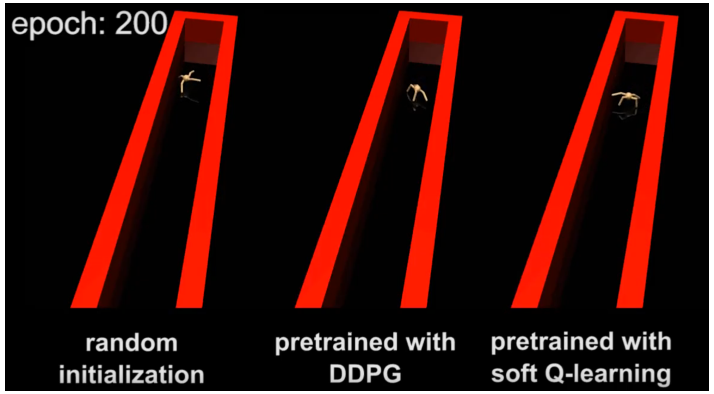

Fine Tune: reward speed in specific direction

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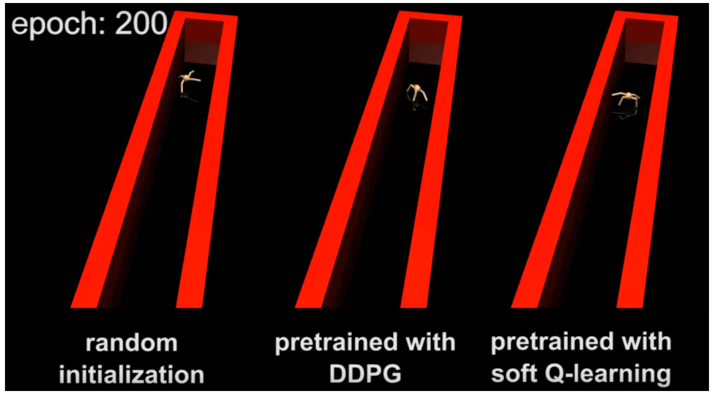


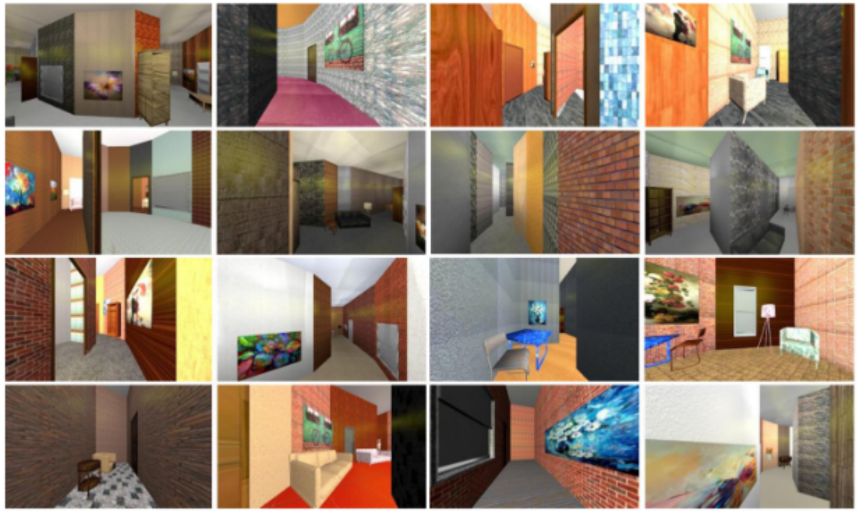
Fine Tune: reward speed in specific direction

Both reward + entropy

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

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

CAD2RL



Key: Diversity

Actor Mimic

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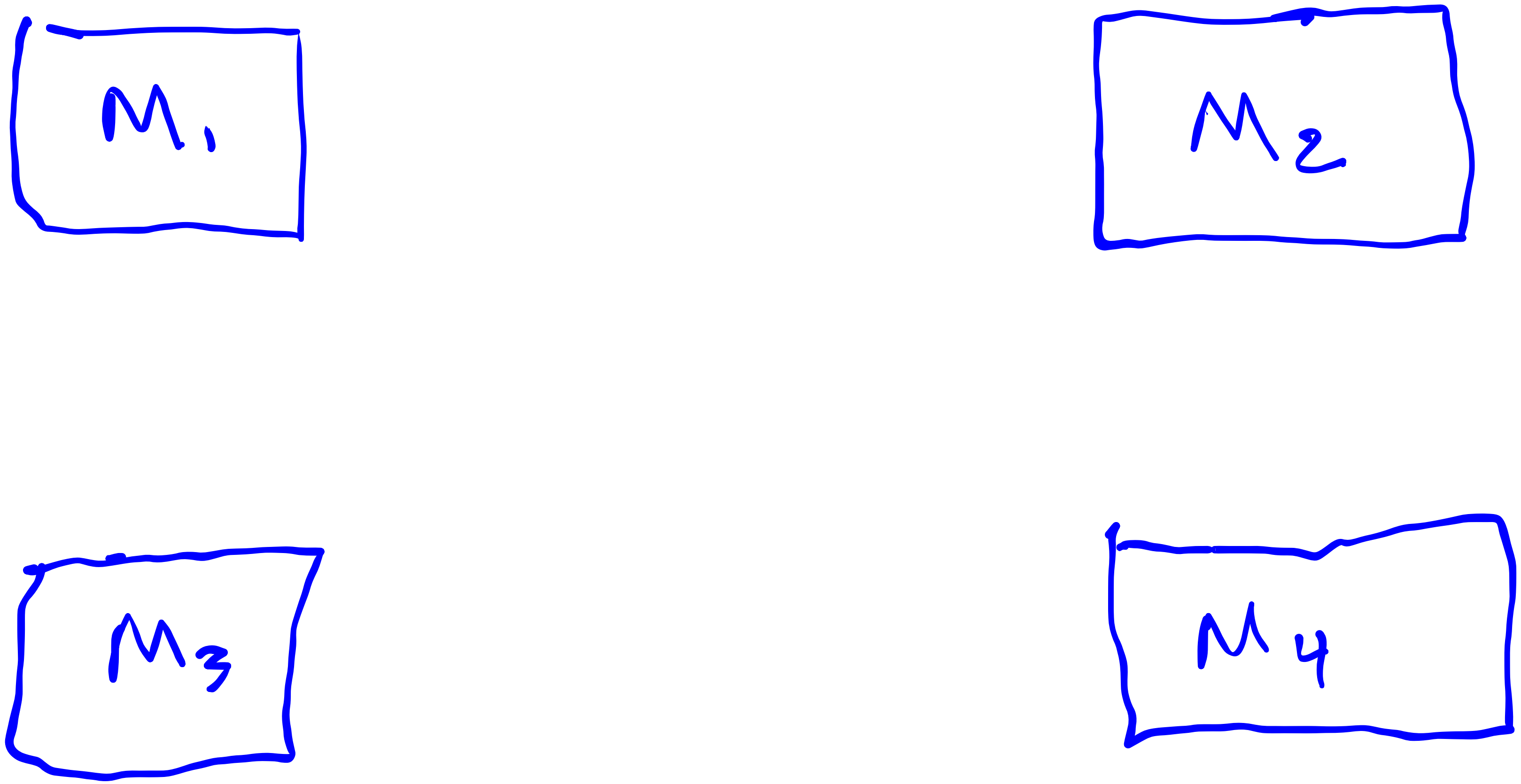

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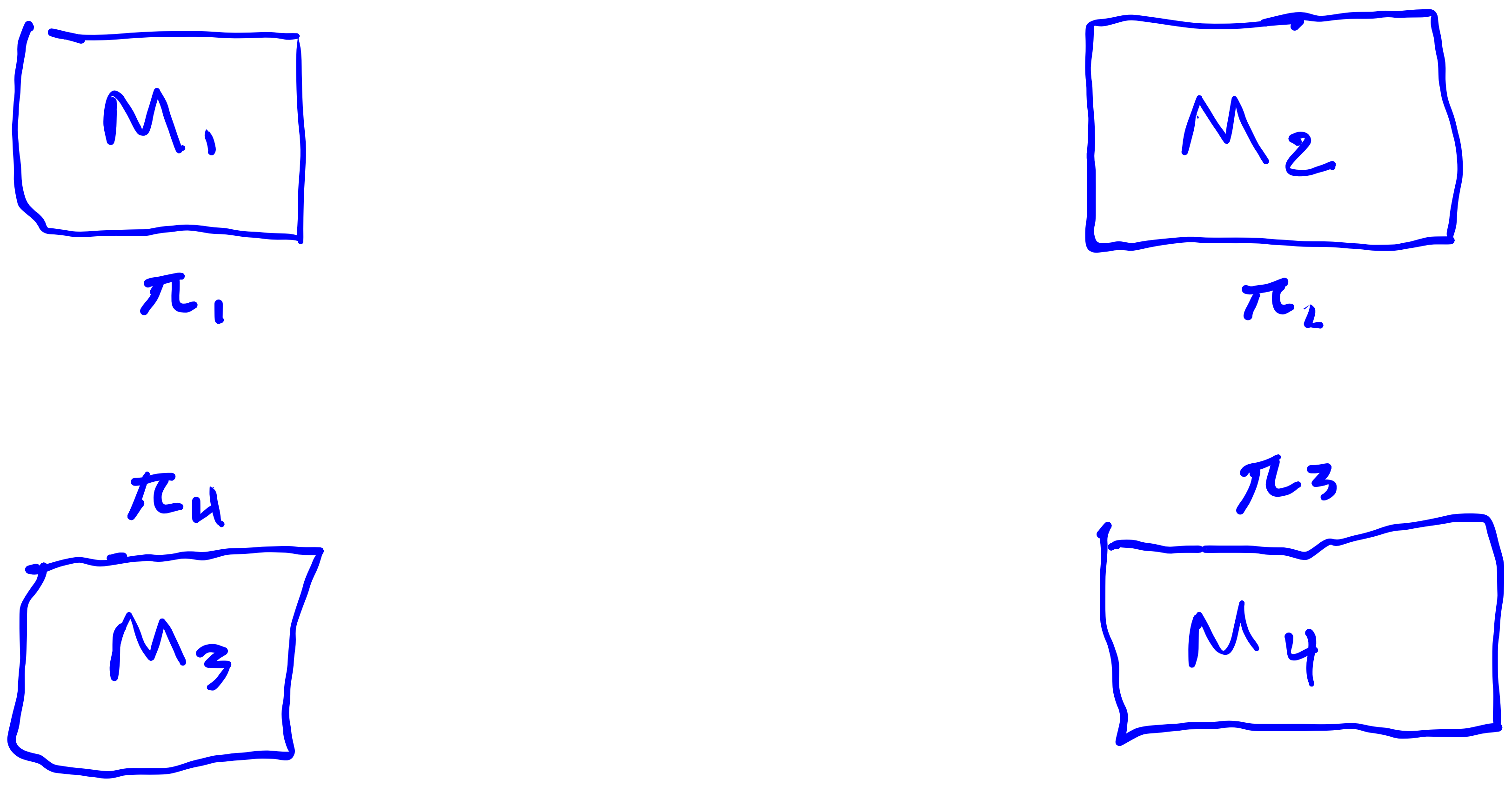

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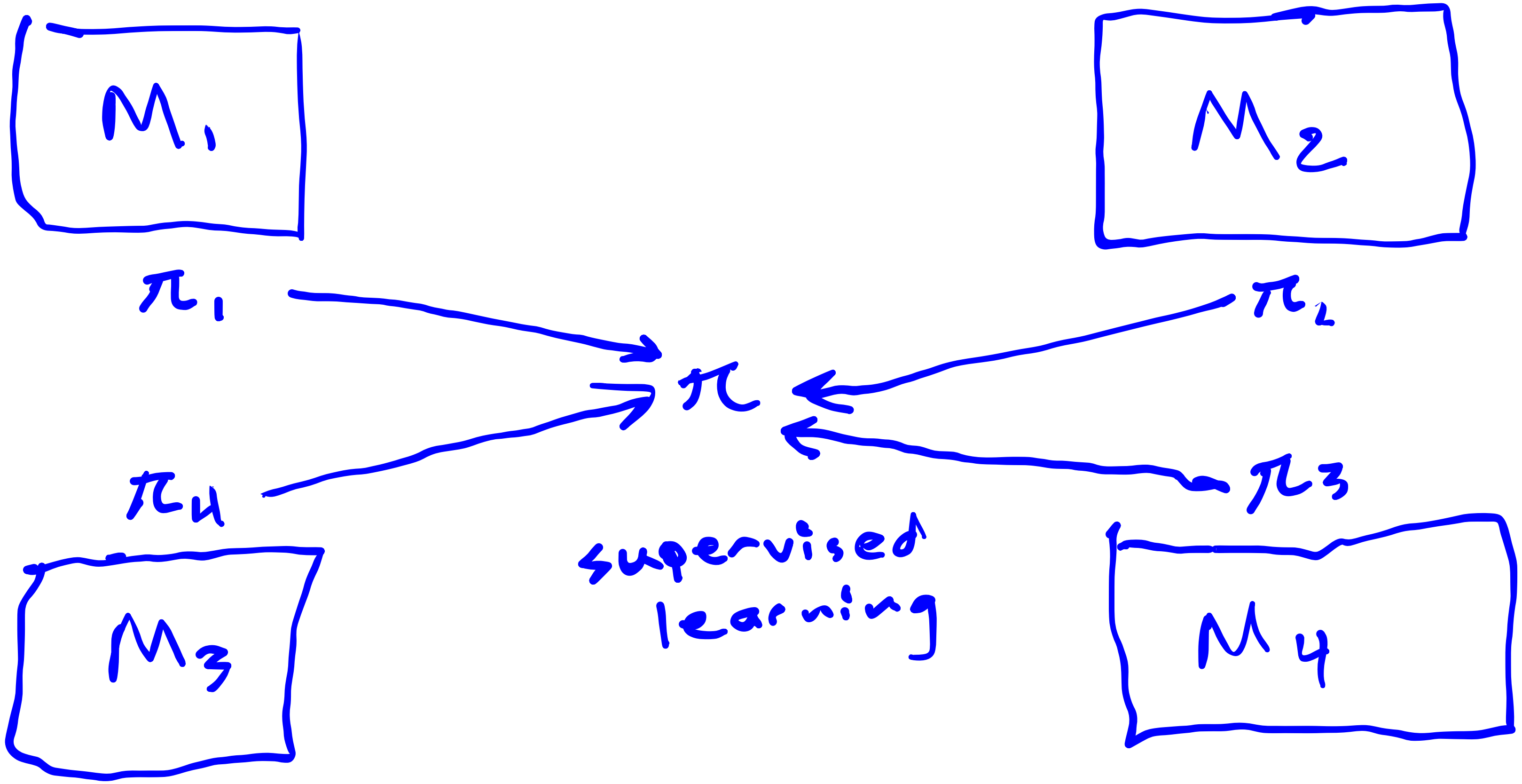

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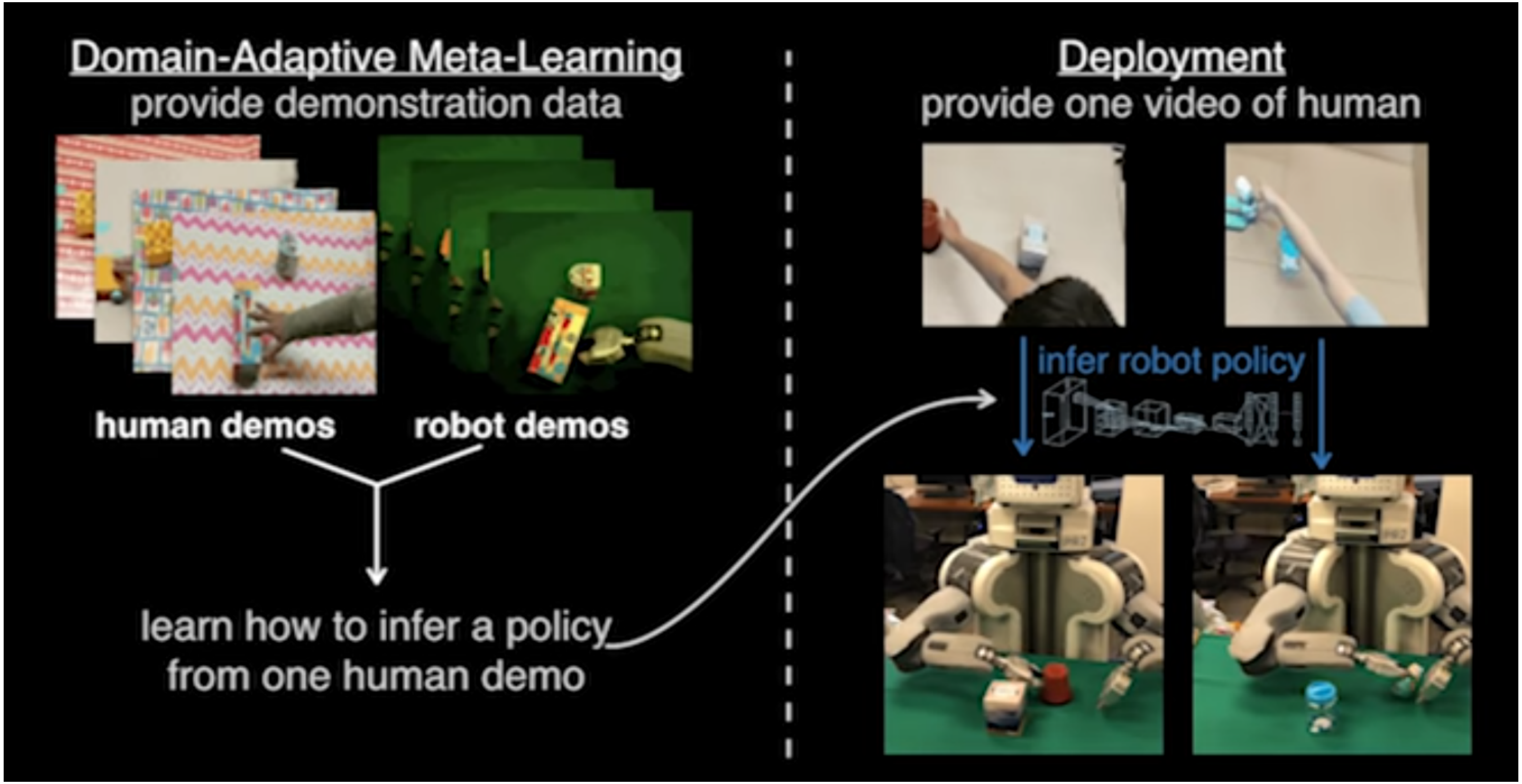
- In target domain, start with best policy from this set and finetune/plan online

Meta Learning: Motivation



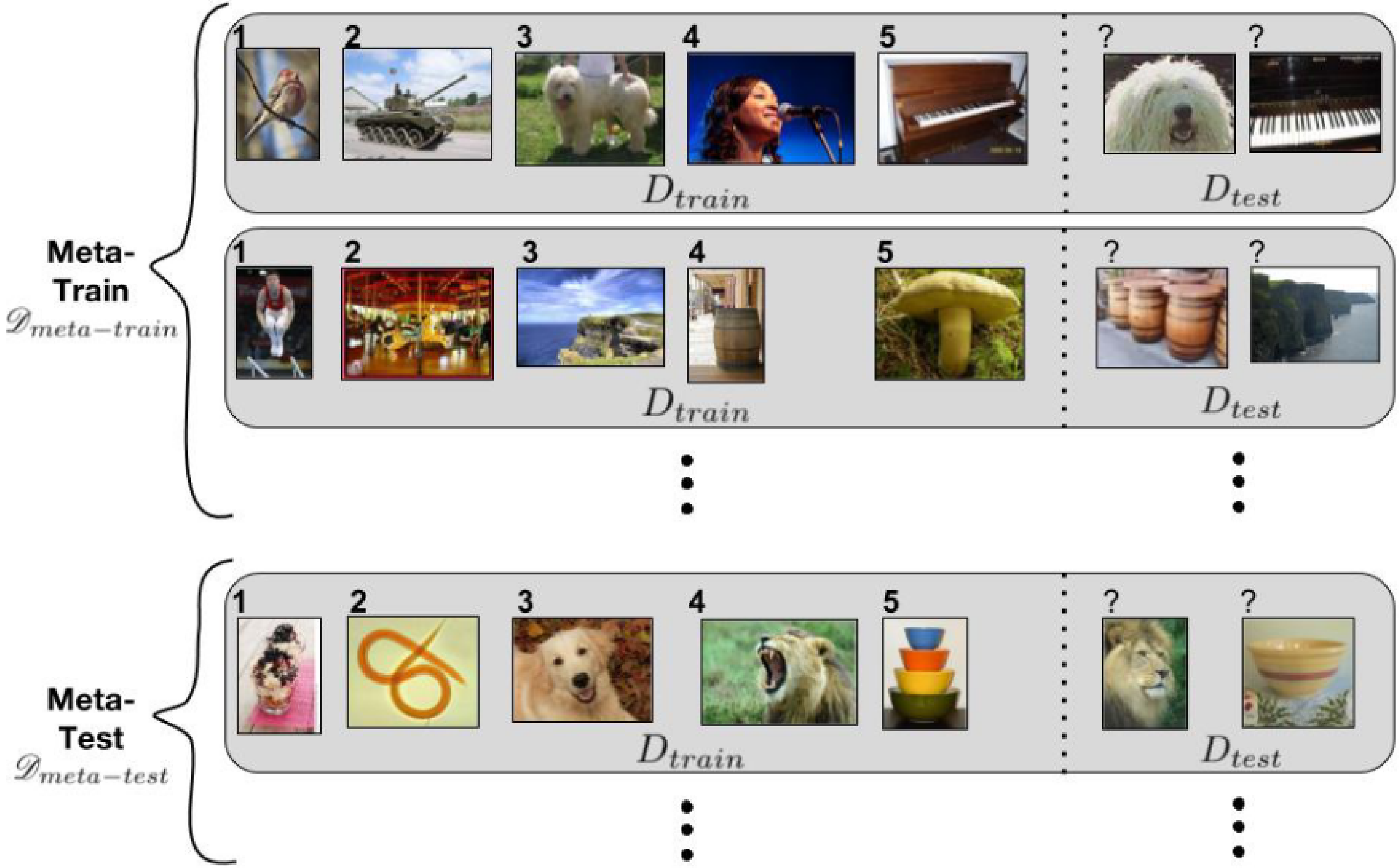
https://www.youtube.com/watch?v=1eYqV_vGlJY

Meta Learning

Meta Learning

Machine
Learning
Data Set

Meta Learning



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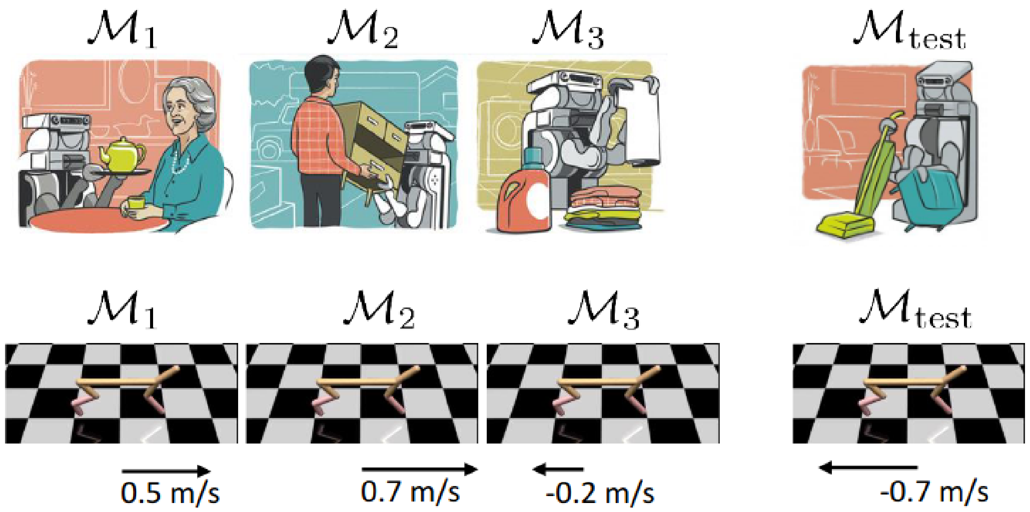

Image: Sergey Levine CS285 slides

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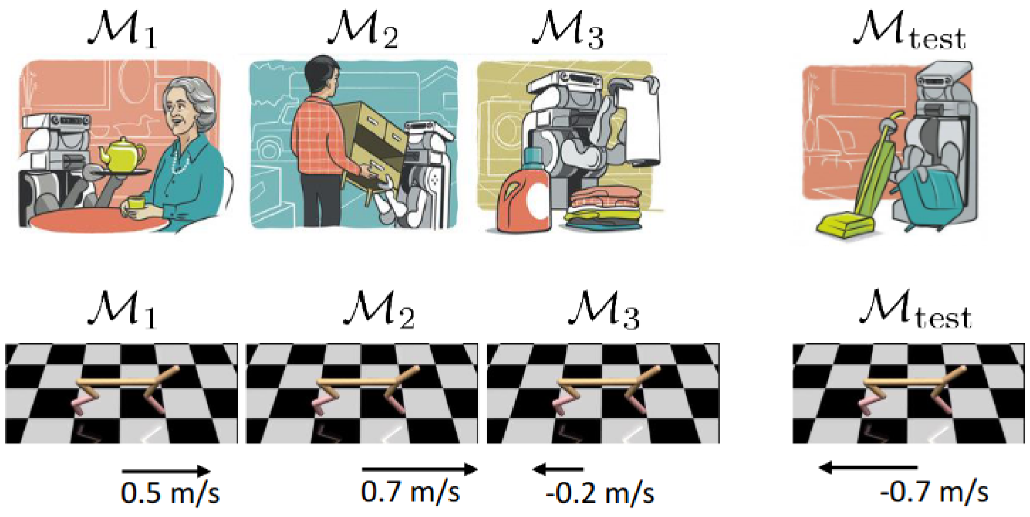

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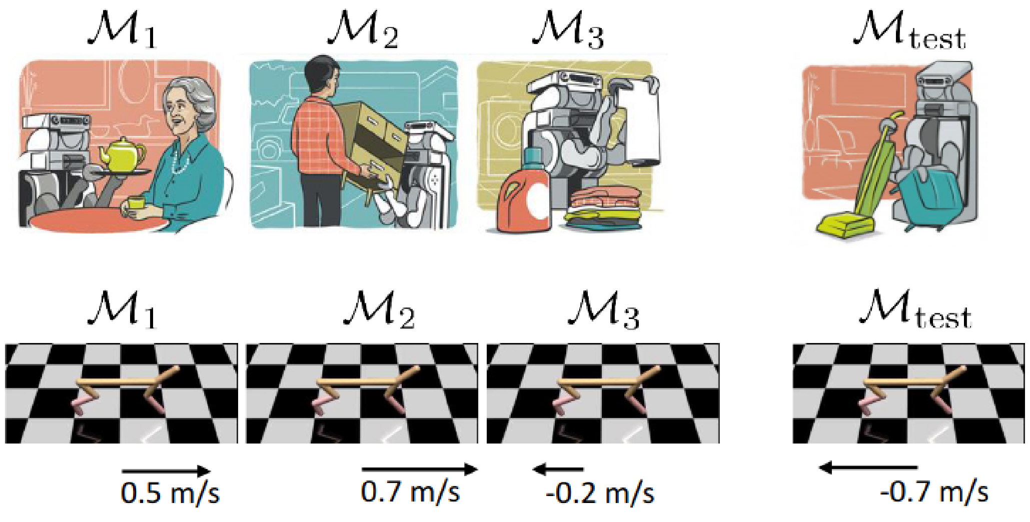

Image: Sergey Levine CS285 slides

Important: Exploration can speed up Meta RL

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

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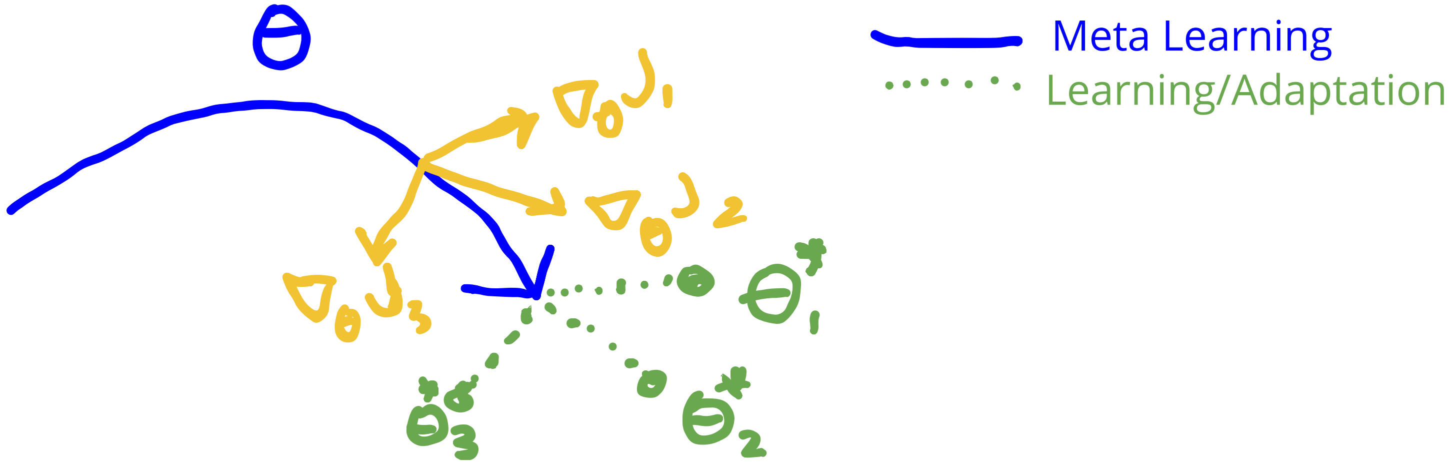

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- A meta learning problem can be posed as a **POMDP**.
- In model agnostic meta learning (**MAML**), the policy is parameterized so that **one gradient step** in the new environment will produce a good policy.