

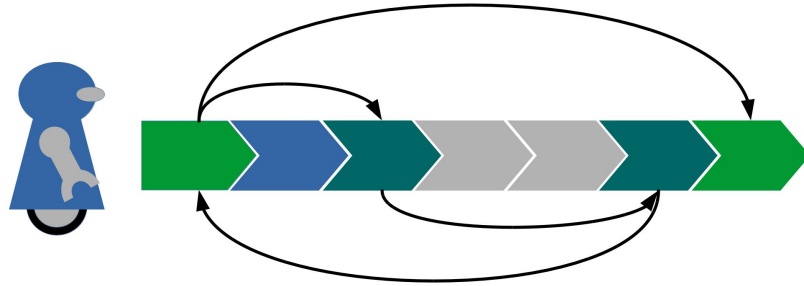
Successor Features for Transfer in Reinforcement Learning

André Barreto Will Dabney Rémi Munos Jonathan Hunt Tom Schaul David Silver Hado van Hasselt

Poster #9 at Pacific Ballroom

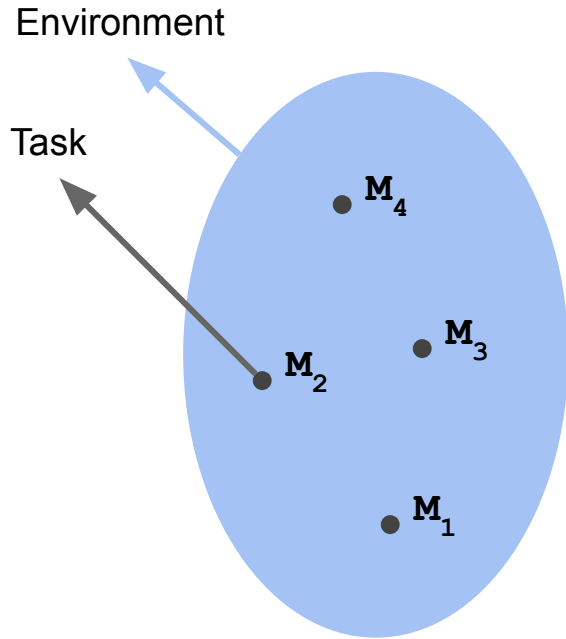


Transfer in Reinforcement Learning



- **Goal:** general framework for transfer in RL
- Fundamental design principles:
 - Exchange of information should take place whenever useful
 - Transfer should be seamlessly integrated within the RL process

Problem definition



- Environment is a **set** of MDPs
- Each MDP M_i is a **task**
- The only difference between the MDPs is the **reward function** r_i :

$$r_i(s, a, s') = \phi(s, a, s')^\top \mathbf{w}_i$$

Proposed solution

Our solution builds on two ideas:

- Generalised policy improvement (GPI)
- Successor features (SFs)

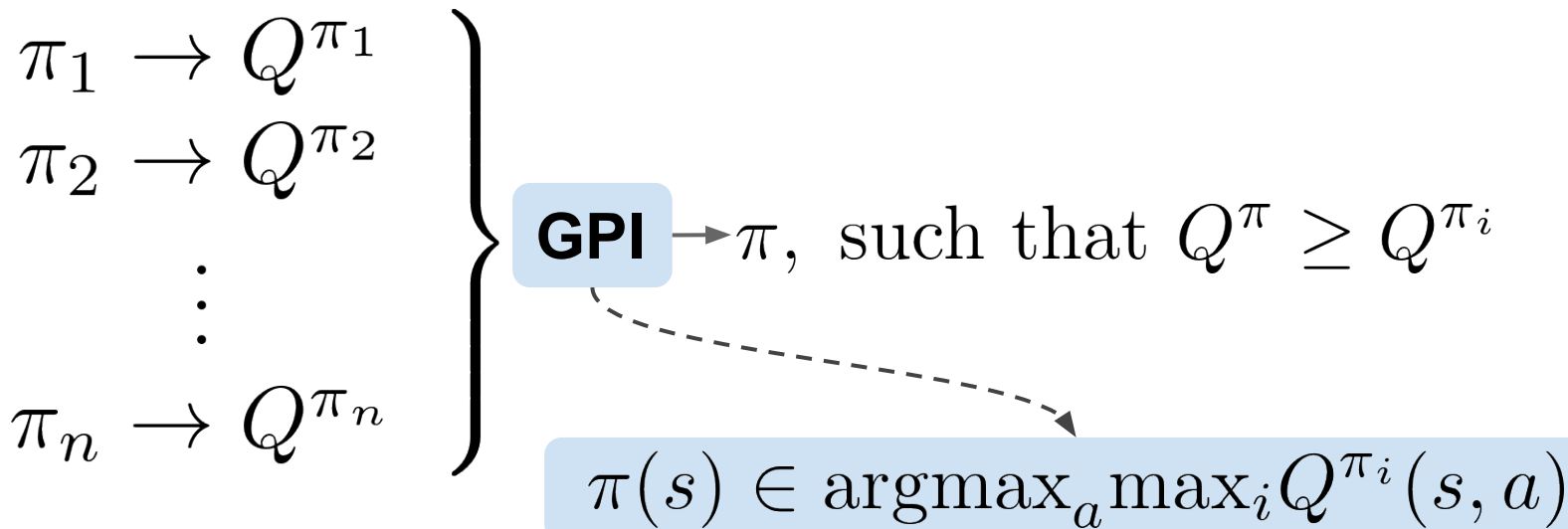
Generalised policy improvement

For a fixed reward function:

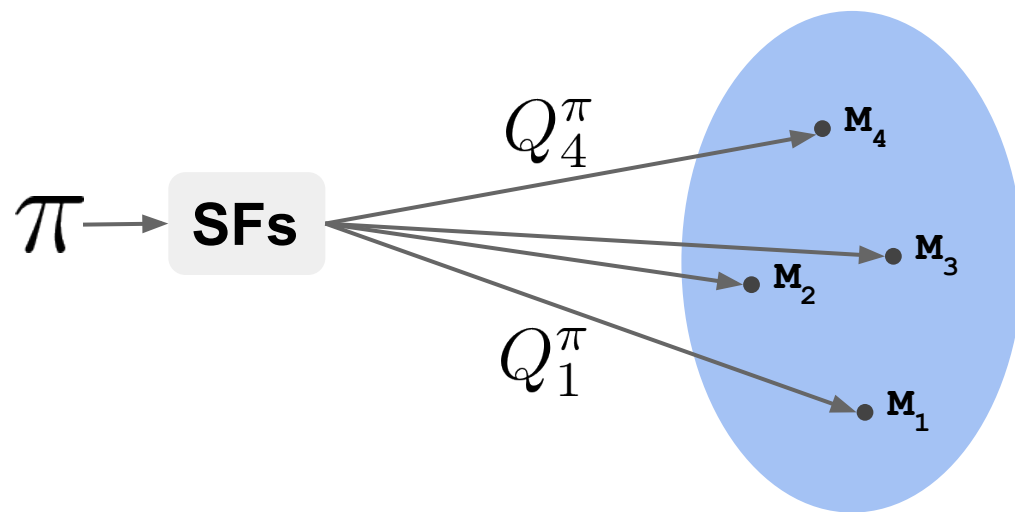
$$\left. \begin{array}{l} \pi_1 \rightarrow Q^{\pi_1} \\ \pi_2 \rightarrow Q^{\pi_2} \\ \vdots \\ \pi_n \rightarrow Q^{\pi_n} \end{array} \right\} \text{GPI} \rightarrow \pi, \text{ such that } Q^\pi \geq Q^{\pi_i}$$

Generalised policy improvement

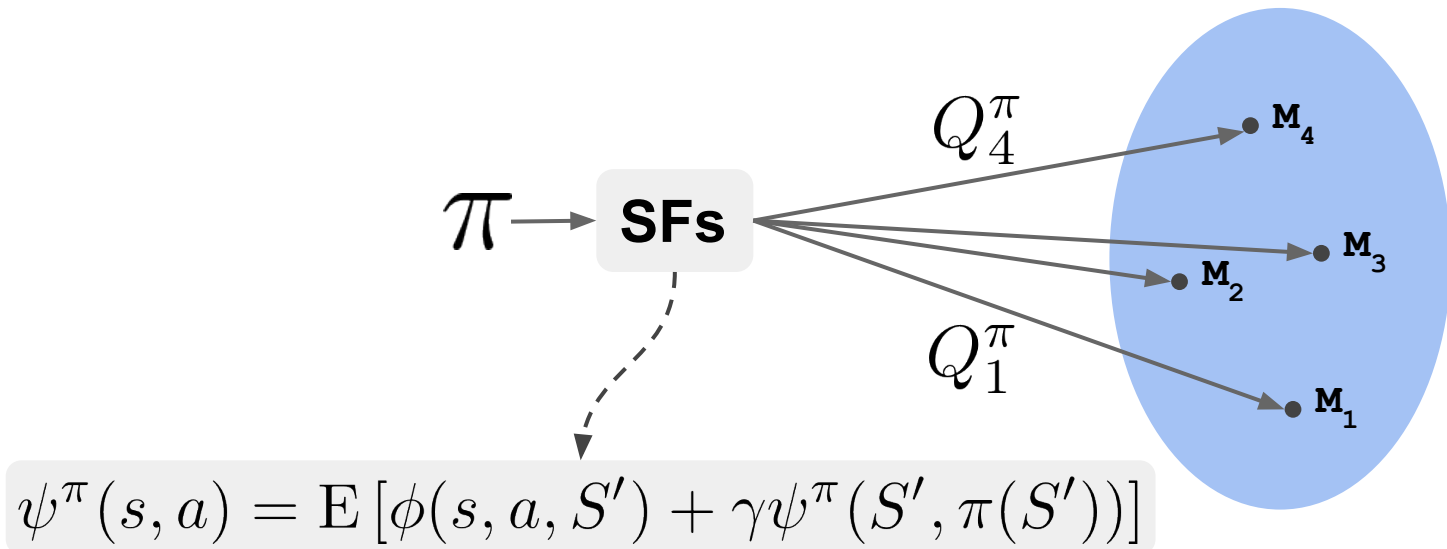
For a fixed reward function:



Successor Features

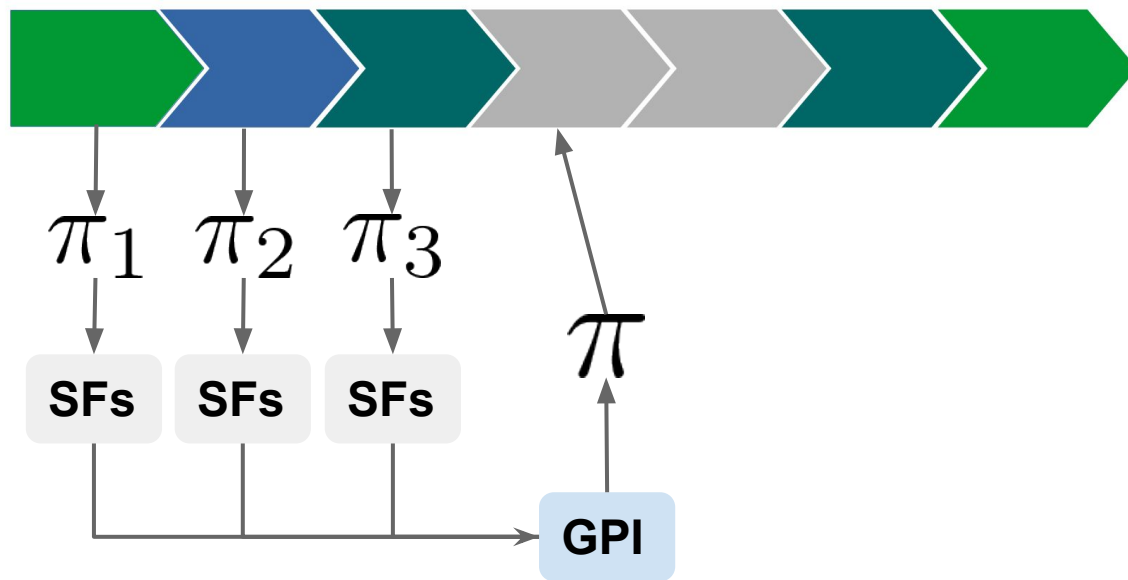


Successor Features

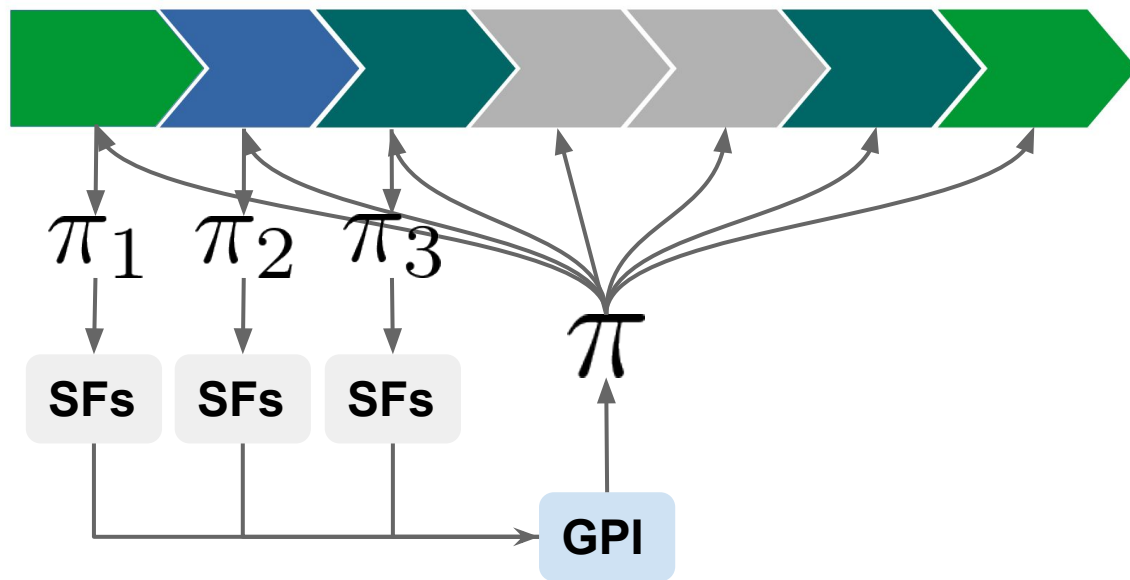


$$Q^\pi(s, a) = \psi^\pi(s, a)^\top \mathbf{w}$$

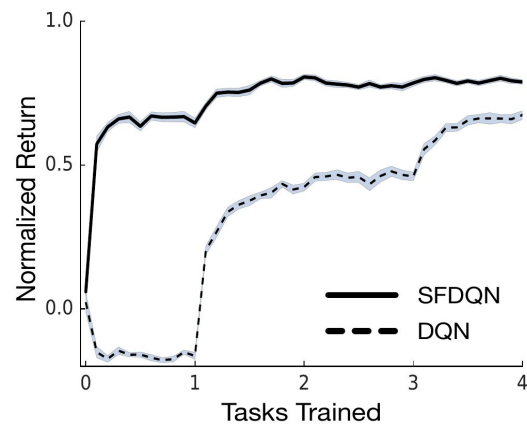
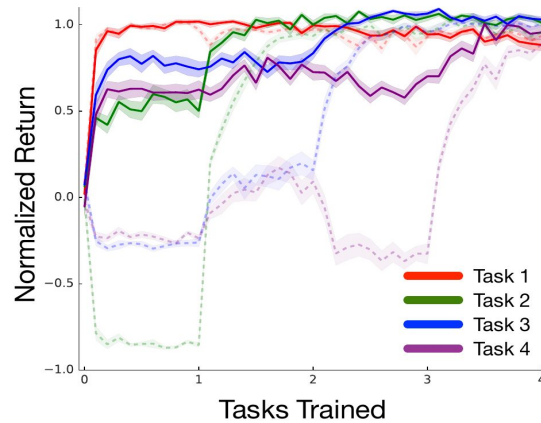
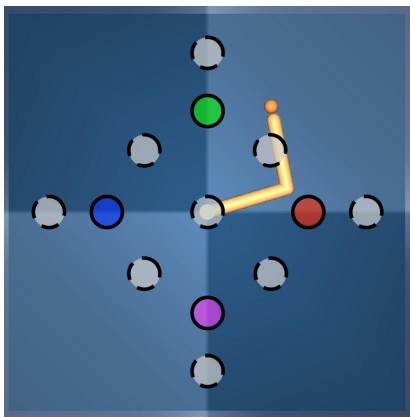
SFs + GPI



SFs + GPI



SFs + GPI



Generalisation across tasks (seen and novel)

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