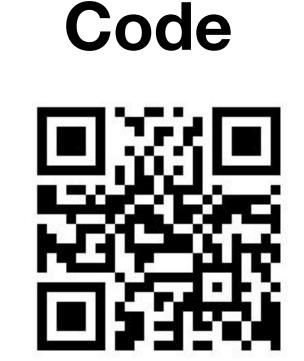


Unsupervised Domain Adaptation with Shared Latent Dynamics for Reinforcement Learning

Paper



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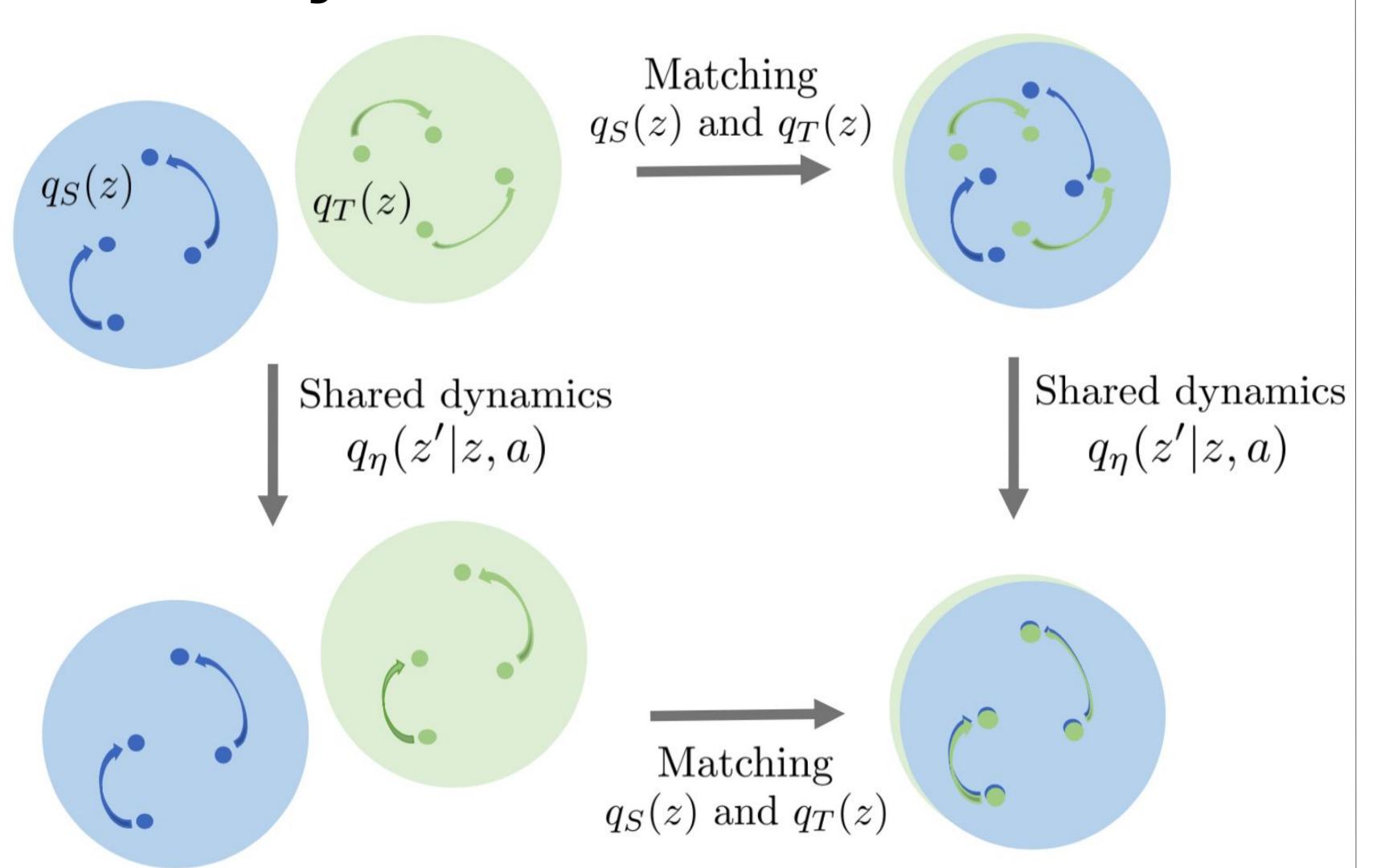
Main points

- Given source and target environments that have similar underlying dynamics
- The goal is to adapt a policy trained on the source

- Moscow

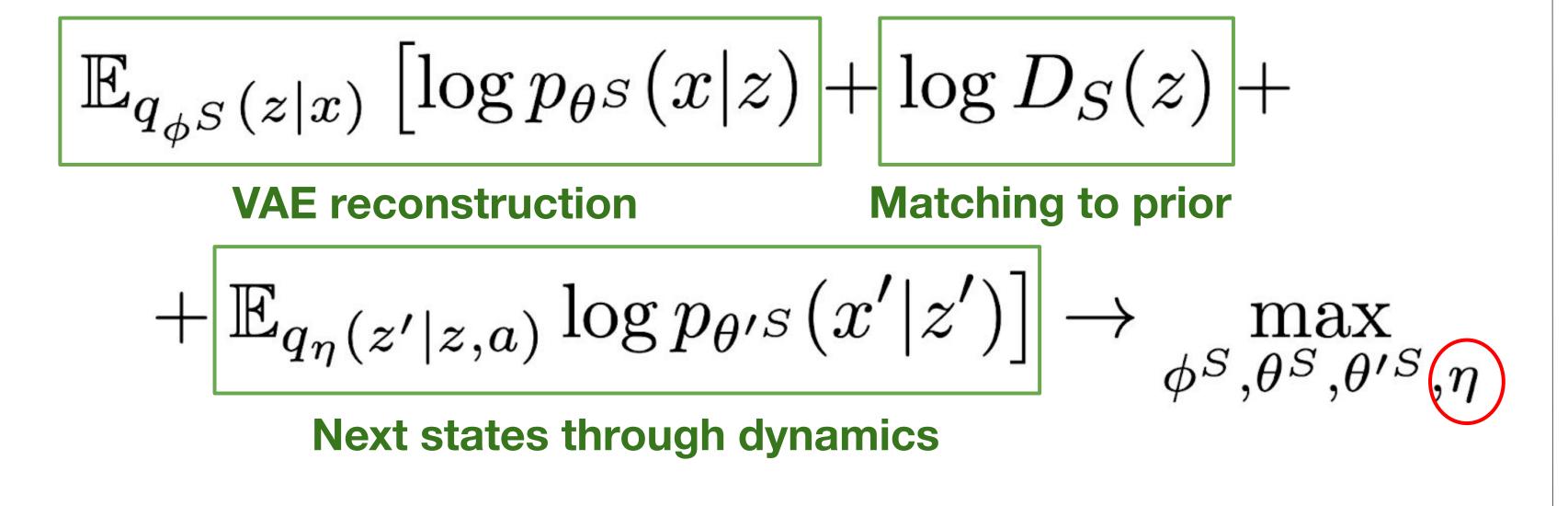
 No access to 1-to-1 correspondence between observations

Alignment of latent codes: shared dynamics and adversarial loss



Training pipeline

1. Learning encoding and dynamics on source



2. Learning policy on top of latent codes

$$\mathbb{E}_{q_{\phi^S}(z|x)} \log \pi_{\xi}(a|z) \to \max_{\xi}$$
 Behavior cloning

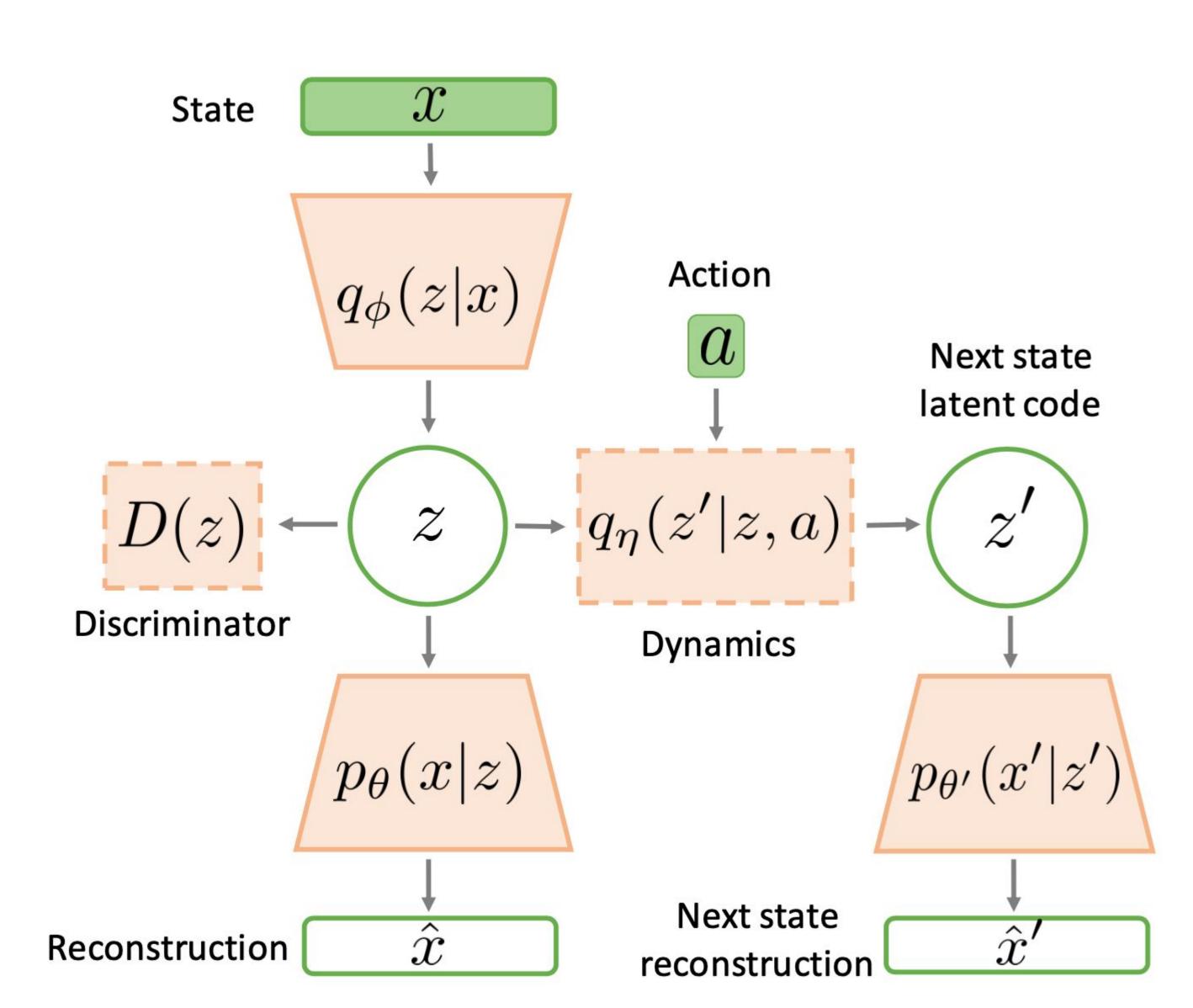
3. Align representations of a new environment

$$\begin{split} \mathbb{E}_{q_{\phi^T}(z|x)} \left[\log p_{\theta^T}(x|z) + \log D_T(z) + \\ \text{VAE reconstruction} \quad & \mathsf{q_s(z) and q_T(z) matching} \\ & + \mathbb{E}_{q_{\eta}(z'|z,a)} \log p_{\theta'^T}(x'|z') \right] \rightarrow \max_{\phi^T,\theta^T,\theta'^T} \\ & \text{Next states, dynamics is fixed} \end{split}$$

Method Summary

- An autoencoding architecture for domain adaptation in RL
- Alignment of latent representations of states via
 - learning shared dynamics
 - o matching aggregated posteriors of latent codes
- A policy trained on the latent representations acts optimally for a target environment

The proposed architecture



Experiments on a toy environment

$$x-\text{MNIST} \quad a \in \{-90^\circ, 0^\circ, +90^\circ\}$$

$$r=+1 \text{ for a correct rotation}$$
 Target environment — digits with inverted colors

Ablation of different model parts

	Const	VAE	Adversarial	Dynamics	Model
Reward	0.40 ± 0	0.40 ± 0.03	0.45 ± 0.06	0.54 ± 0.07	0.81 ± 0.21

Cross-reconstructions for trained source and target models

