Carnegie Mellon

School of Computer Science

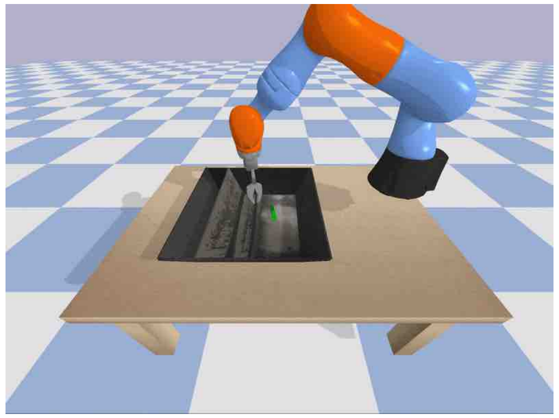
Deep Reinforcement Learning and Control

Multigoal RL, Goal Relabeling

Spring 2020, CMU 10-403

Katerina Fragkiadaki

So far we train one policy/value function per task, e.g., win the game of Tetris, win the game of Go, reach to a *particular* location, put the green cube inside the gray bucket, etc.



Universal value function Approximators

$$V(s;\theta) \rightarrow V(s,g;\theta)$$

$$\pi(s;\theta) \rightarrow \pi(s,g;\theta)$$

- All methods we have learnt so far can be used.
- At the beginning of an episode, we sample not only a start state but also a goal g, which stays constant throughout the episode
- The experience tuples should contain the goal.

$$(s,a,r,s') \rightarrow (s,g,a,r,s')$$

Universal Value Function Approximators, Schaul et al.

Universal value function Approximators

$$V(s, \theta) \rightarrow V(s, g; \theta)$$

$$\pi(s; \theta) \rightarrow \pi(s, g; \theta)$$

What should be my goal representation?

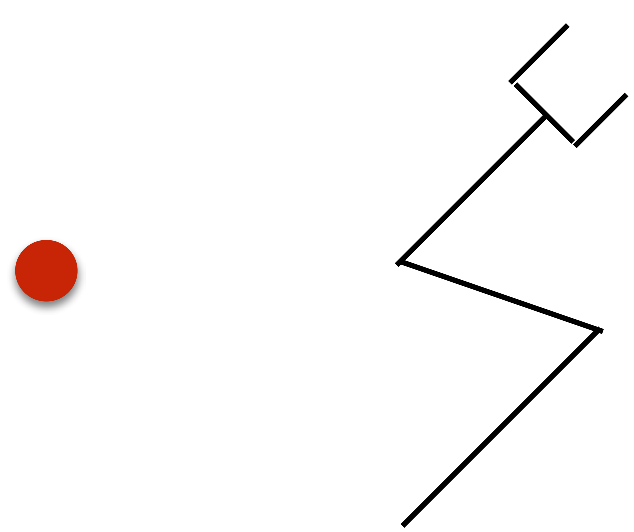
The goal representation is usually the same as your state representation.
Usually one of the two:

- Manual/oracle: 3d centroids of objects, robot joint angles and velocities, 3d location of the gripper, etc.
- Learnt: Some feature encoding of a goal image

Hindsight Experience Replay

Marcin Andrychowicz*, Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, Pieter Abbeel†, Wojciech Zaremba†
OpenAI

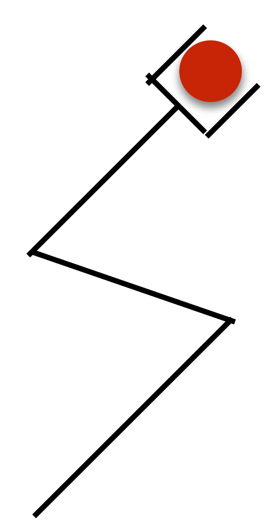
Main idea: use failed executions under one goal g, as successful executions under an alternative goal g' (which is where we ended at the end of the episode).



No reward :-(

Goal g

Our reacher at the end of the episode $(s, g, a, 0, s')$



Goal g'

reward :-)

Our reacher at the end of the episode $(s, g', a, 1, s')$

Hindsight Experience Replay

Marcin Andrychowicz[*], Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, Pieter Abbeel[†], Wojciech Zaremba[†]
OpenAI

Main idea: use failed executions under one goal g, as successful executions under an alternative goal g' (which is where we ended at the end of the episode).

Hindsight Experience Replay

Algorithm 1 Hindsight Experience Replay (HER)

Given:

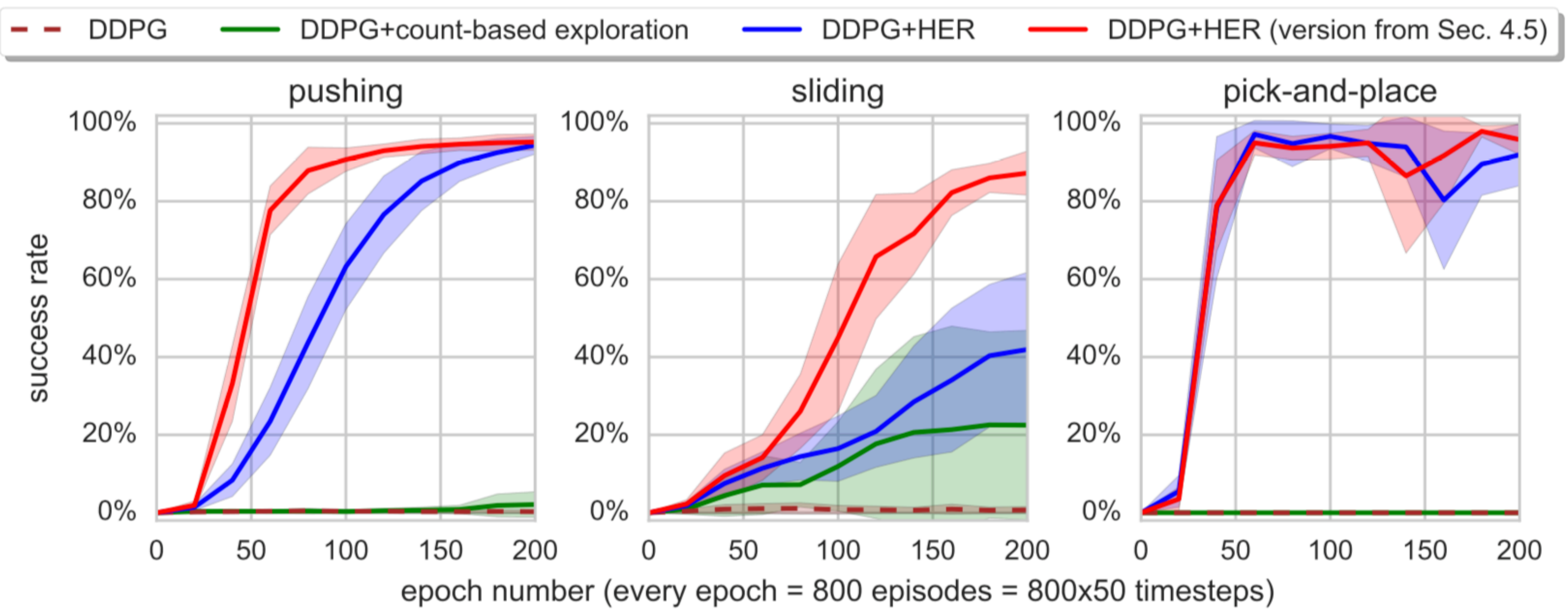
- an off-policy RL algorithm $\mathbb{A}$, $\triangleright$ e.g. DQN, DDPG, NAF, SDQN
- a strategy $\mathbb{S}$ for sampling goals for replay, $\triangleright$ e.g. $\mathbb{S}(s_0, \ldots, s_T) = m(s_T)$
- a reward function $r : \mathcal{S} \times \mathcal{A} \times \mathcal{G} \to \mathbb{R}$. $\triangleright$ e.g. $r(s, a, g) = -[f_g(s) = 0]$

Initialize $\mathbb{A}$ $\triangleright$ e.g. initialize neural networks
Initialize replay buffer R
for episode $= 1, M$ **do**
  Sample a goal g and an initial state s_0.
  for $t = 0, T-1$ **do**
    Sample an action a_t using the behavioral policy from $\mathbb{A}$:
      $a_t \leftarrow \pi_b(s_t || g)$ $\triangleright$ $||$ denotes concatenation
    Execute the action a_t and observe a new state s_{t+1}
  end for
  for $t = 0, T-1$ **do**
    $r_t := r(s_t, a_t, g)$
    Store the transition $(s_t || g, a_t, r_t, s_{t+1} || g)$ in R $\triangleright$ standard experience replay
    Sample a set of additional goals for replay $G := \mathbb{S}(\textbf{current episode})$
    for $g' \in G$ **do**
      $r' := r(s_t, a_t, g')$
      Store the transition $(s_t || g', a_t, r', s_{t+1} || g')$ in R $\triangleright$ HER
    end for
  end for
  for $t = 1, N$ **do**
    Sample a minibatch B from the replay buffer R
    Perform one step of optimization using $\mathbb{A}$ and minibatch B
  end for
end for

G : the states of the current episode

Usually as additional goal we pick the goal that this episode achieved, and the reward becomes non zero

Hindsight Experience Replay



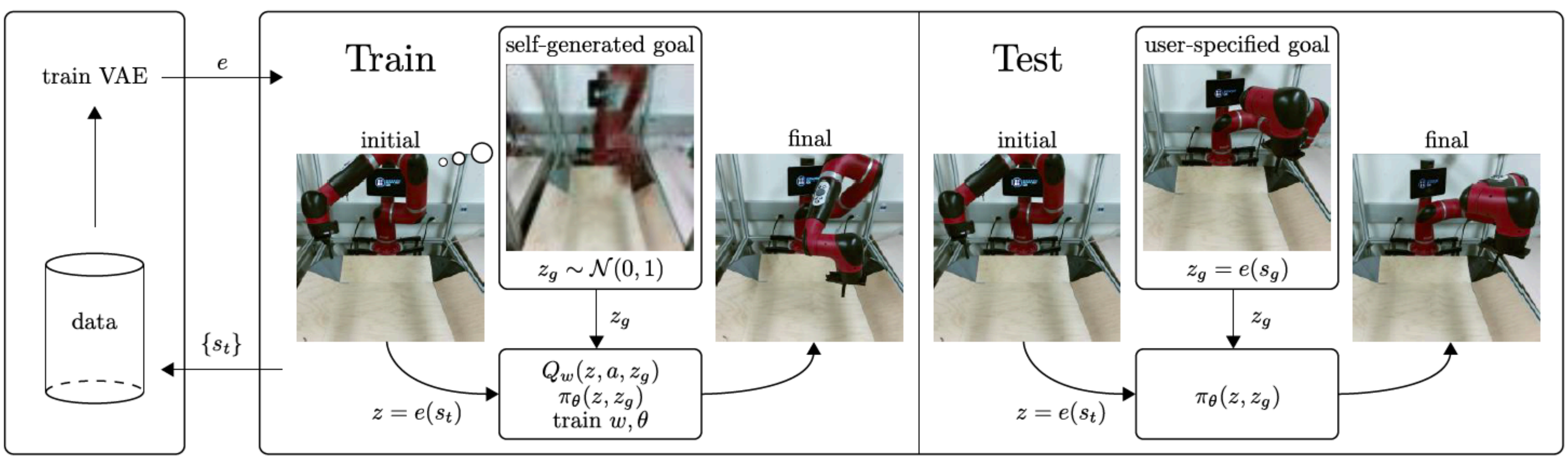
Visual Reinforcement Learning with Imagined Goals

Ashvin Nair*, Vitchyr Pong*, Murtaza Dalal, Shikhar Bahl, Steven Lin, Sergey Levine
University of California, Berkeley
{anair17,vitchyr,mdalal,shikharbahl,stevenlin598,svlevine}@berkeley.edu

Main ideas:
- Train a generative model of images that maps low-dim latent code sampled from a fixed Gaussian distribution to images.
- Use that latent code as the state and goal representation.
- Sample goals from that generative model for goal relabelling (augmenting experience)
- Use L2 distance over latent codes as the (inverse of) reward function.
- Retrain the generative model as the policy changes and the agent visits different parts of the state space

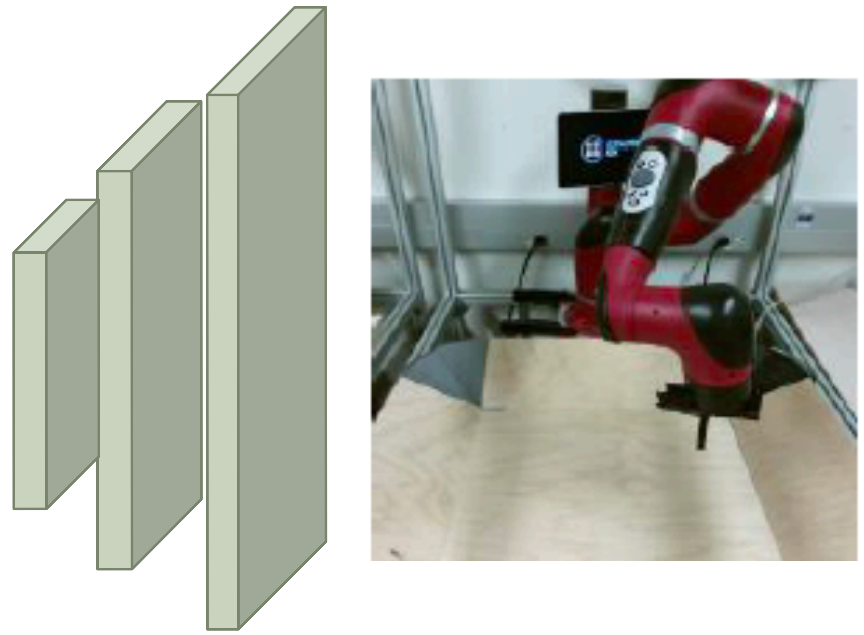
Visual Reinforcement Learning with Imagined Goals

Ashvin Nair*, Vitchyr Pong*, Murtaza Dalal, Shikhar Bahl, Steven Lin, Sergey Levine
University of California, Berkeley
{anair17,vitchyr,mdalal,shikharbahl,stevenlin598,svlevine}@berkeley.edu

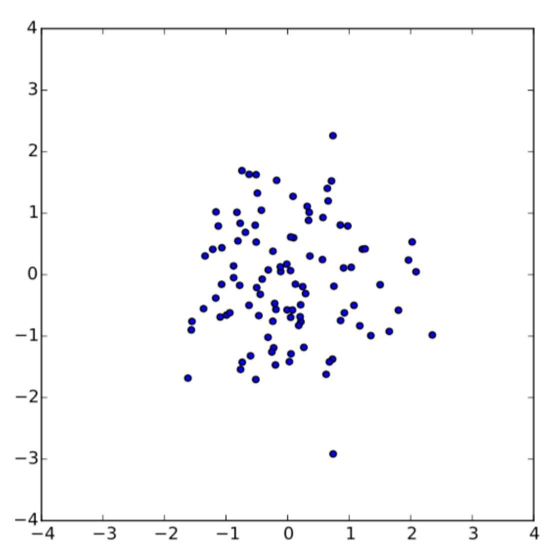


Learning Generative models of images

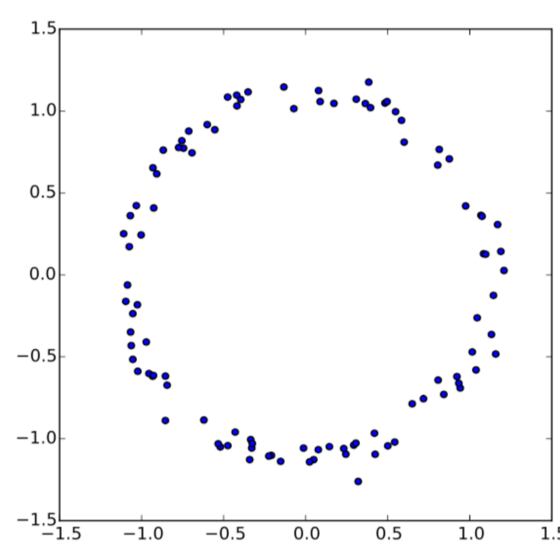
$z \sim \mathcal{N}(\mathbf{0}, I)$



- Why simple gaussian noise suffices to create complex outputs?
- The neural net will transform it to a complex distribution!

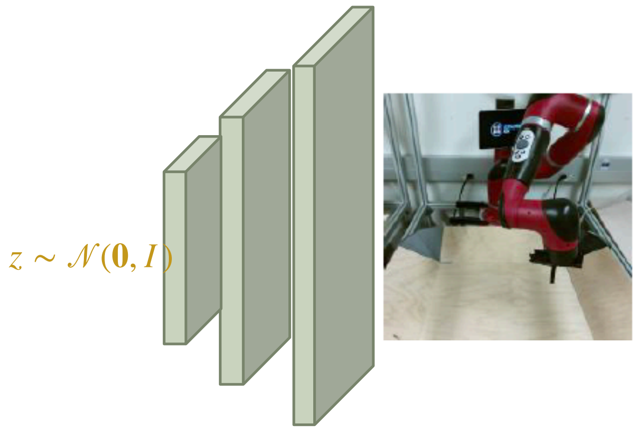


$$z \sim \mathcal{N}(\mathbf{0}, I)$$



$$f(z) = \frac{z}{10} + \frac{z}{\|z\|}$$

Training Networks with Stochastic Units



Each sample z should give me a realistic image X once it passes through the neural network

We want to learn a mapping from z to the **output image X**, usually we assume a Gaussian distribution to sample every pixel from:

$$P(X \mid z; \theta) = \mathcal{N}(X \mid f(z; \theta), \sigma^2 \cdot I)$$

Let's maximize data likelihood. This requires an intractable integral, too many zs..

$$\max_{\theta} . \quad P(X) = \int P(X \mid z; \theta) P(z) dz$$

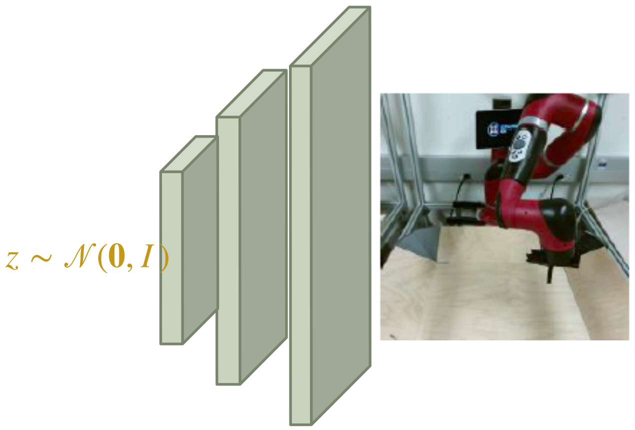
What if we forget that it is intractable and approximate it with few samples?

$$\min_{\theta} . \quad \sum_j -\log P(X_j) = -\sum_j \sum_{z_i \sim \mathcal{N}(\mathbf{0}, I)} \log P(X_j \mid z; \theta) = -\sum_j \sum_{z_i \sim \mathcal{N}(\mathbf{0}, I)} \|f(z_i; \theta) - X_j\|^2$$

(Q: do we know how to take gradients here?)

Motion Prediction Under Multimodality with Conditional Stochastic Networks, Google

Training Networks with Stochastic Units



Each sample z should give me a realistic image X once it passes through the neural network

We want to learn a mapping from z to the **output image X**, usually we assume a Gaussian distribution to sample every pixel from:

$$P(X \mid z; \theta) = \mathcal{N}(X \mid f(z; \theta), \sigma^2 \cdot I)$$

Let's maximize data likelihood. This requires an intractable integral, too many zs..

$$\max_{\theta} . \quad P(X) = \int P(X \mid z; \theta) P(z) dz$$

What if we forget that it is intractable and approximate it with few samples?

(Q: do we know how to take gradients here?)

$$\min_{\theta} . \quad \sum_j -\log P(X_j) = -\sum_j \sum_{z_i \sim \mathcal{N}(\mathbf{0}, I)} \log P(X_j \mid z; \theta) = -\sum_j \sum_{z_i \sim \mathcal{N}(\mathbf{0}, I)} \|f(z_i; \theta) - X_j\|^2$$

$$\min_{\theta} . \quad -\sum_j \min_{z_i \sim \mathcal{N}(\mathbf{0}, I)} \|f(z_i; \theta) - X_j\|^2$$ K-best loss

Motion Prediction Under Multimodality with Conditional Stochastic Networks, Google

Deep Variational Inference

Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior, $P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$D_{KL}(Q(z|X)||P(z|X)) = \int Q(z|X) \log \frac{Q(z|X)}{P(z|X)} dz$$

Deep Variational Inference

Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior, $P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$\begin{aligned} D_{KL}(Q(z|X)||P(z|X)) &= \int Q(z|X)\log\frac{Q(z|X)}{P(z|X)}dz \\ &= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(z|X) \end{aligned}$$

Deep Variational Inference

Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior, $P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$
\begin{aligned}
D_{KL}(Q(z|X)||P(z|X)) &= \int Q(z|X)\log\frac{Q(z|X)}{P(z|X)}dz \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(z|X) \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)}
\end{aligned}
$$

Deep Variational Inference

Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior, $P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$
\begin{aligned}
D_{KL}(Q(z|X)||P(z|X)) &= \int Q(z|X) \log \frac{Q(z|X)}{P(z|X)} dz \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(z|X) \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)}
\end{aligned}
$$

Deep Variational Inference

Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior,$P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$
\begin{aligned}
D_{KL}(Q(z|X)||P(z|X)) &= \int Q(z|X)\log\frac{Q(z|X)}{P(z|X)}dz \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(z|X) \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(X|z) - \mathbb{E}_Q \log P(z) + \log P(X)
\end{aligned}
$$

Deep Variational Inference

Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior,$P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$\begin{aligned}
D_{KL}(Q(z|X)||P(z|X)) &= \int Q(z|X)\log\frac{Q(z|X)}{P(z|X)}dz \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(z|X) \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(X|z) - \mathbb{E}_Q \log P(z) + \log P(X)
\end{aligned}$$

Deep Variational Inference

Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior,$P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$
\begin{aligned}
D_{KL}(Q(z|X)||P(z|X)) &= \int Q(z|X) \log \frac{Q(z|X)}{P(z|X)} dz \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(z|X) \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(X|z) - \mathbb{E}_Q \log P(z) + \log P(X) \\
&= D_{KL}(Q(z|X)|P(z)) - \mathbb{E}_Q \log P(X|z) + \log P(X)
\end{aligned}
$$

Deep Variational Inference

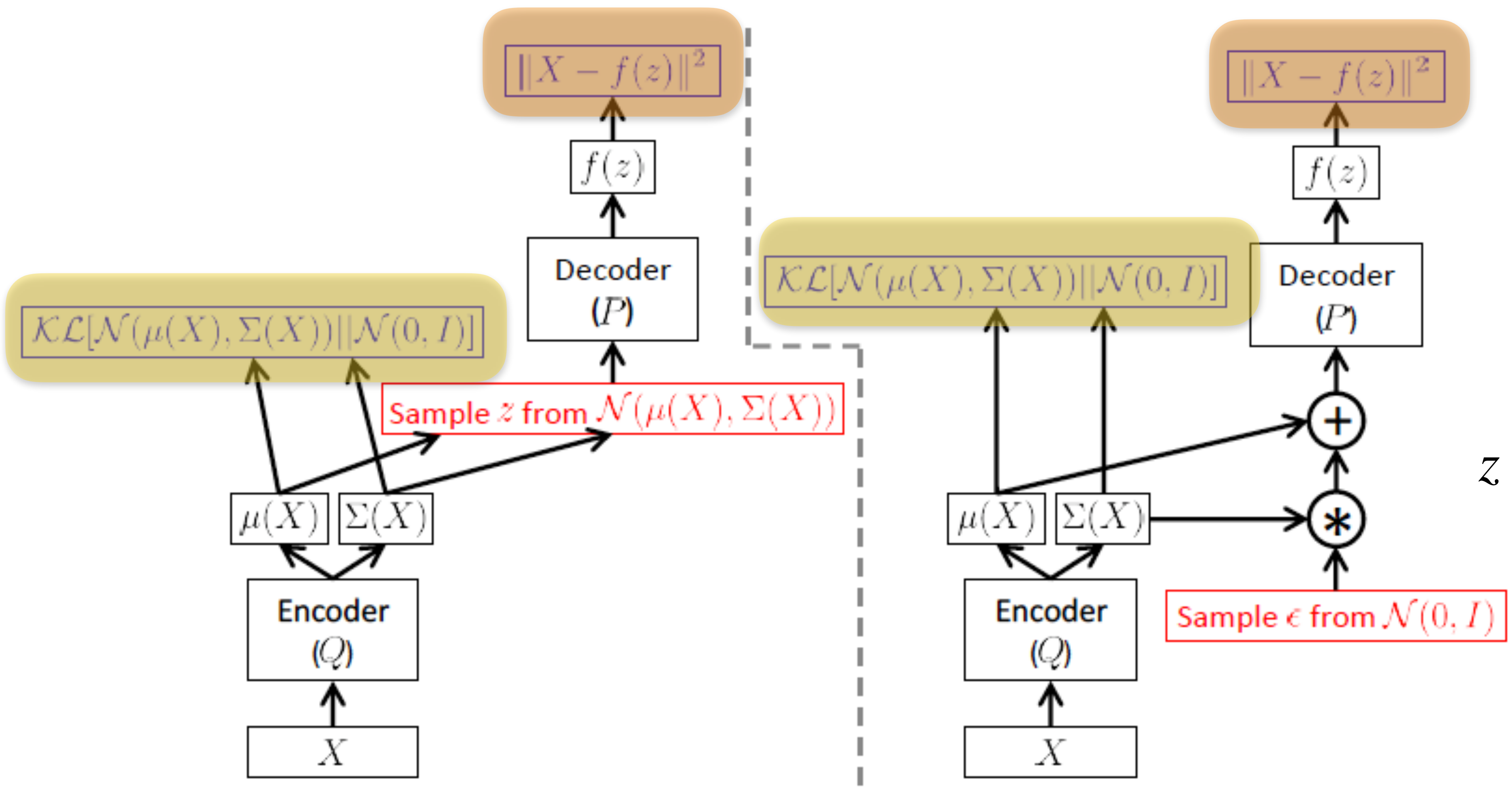
Let's consider sampling z's from an alternative distribution $Q(z)$ and try to minimize the KL between this (variational approximation) and the true posterior, $P(z|X)$. And because I can pick any distribution Q I like, I will also condition it on X to help inform the sampling.

$$
\begin{aligned}
D_{KL}(Q(z|X)||P(z|X)) &= \int Q(z|X)\log\frac{Q(z|X)}{P(z|X)}dz \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(z|X) \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log \frac{P(X|z)P(z)}{P(X)} \\
&= \mathbb{E}_Q \log Q(z|X) - \mathbb{E}_Q \log P(X|z) - \mathbb{E}_Q \log P(z) + \log P(X) \\
&= D_{KL}(Q(z|X)|P(z)) - \mathbb{E}_Q \log P(X|z) + \log P(X)
\end{aligned}
$$

$$
\min_{\phi,\theta}. \quad D_{KL}(\underbrace{Q(z|X;\phi)}_{\text{encoder}}||P(z)) - \mathbb{E}_Q \log \underbrace{P(X|z;\theta)}_{\text{decoder}}
$$

Variational Autoencoder

From left to right: re-parametrization trick!



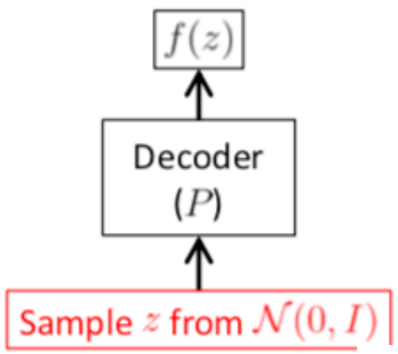
$$z = \mu + \epsilon \cdot \sigma$$

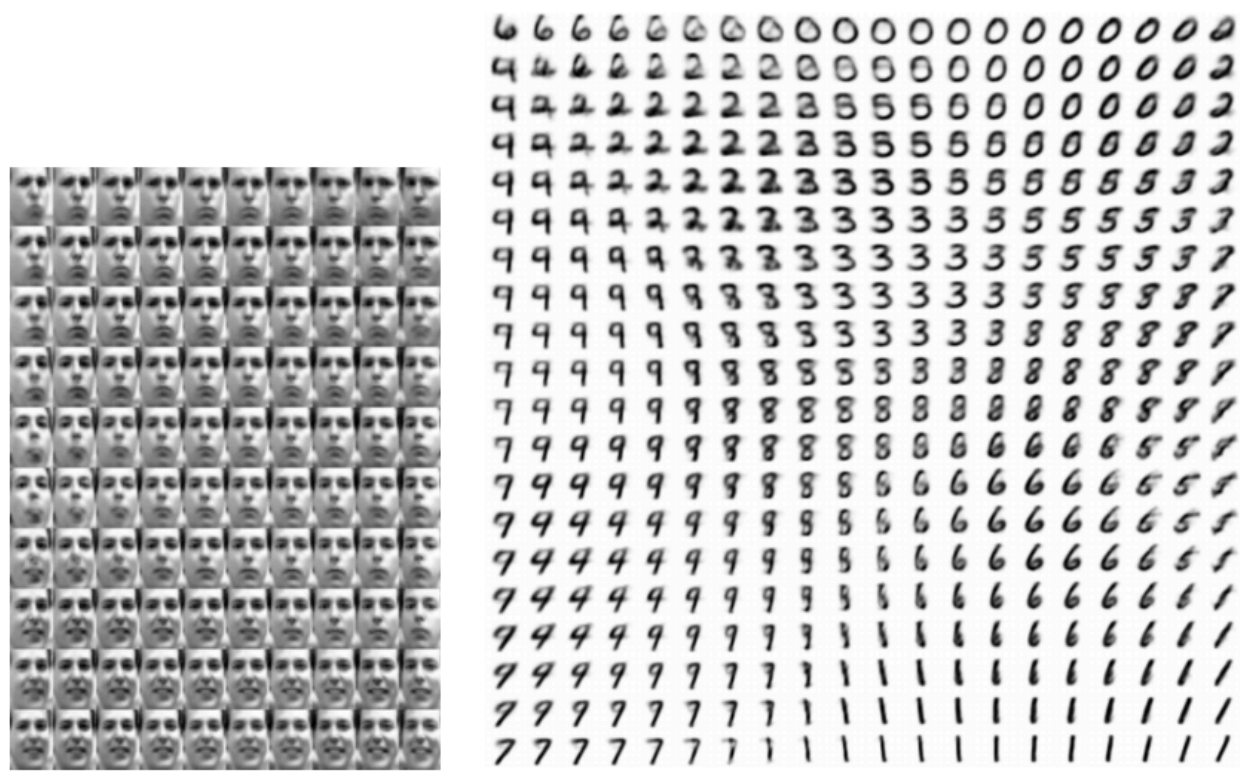
$$\min_{\phi,\theta} . \quad D_{KL}(\underbrace{Q(z \mid X; \phi)}_{\text{encoder}} \mid\mid P(z)) - \mathbb{E}_Q \log \underbrace{P(X \mid z; \theta)}_{\text{decoder}}$$

T*utotial on variational Autoencoders,* Doersch

Variational Autoencoder

At test time

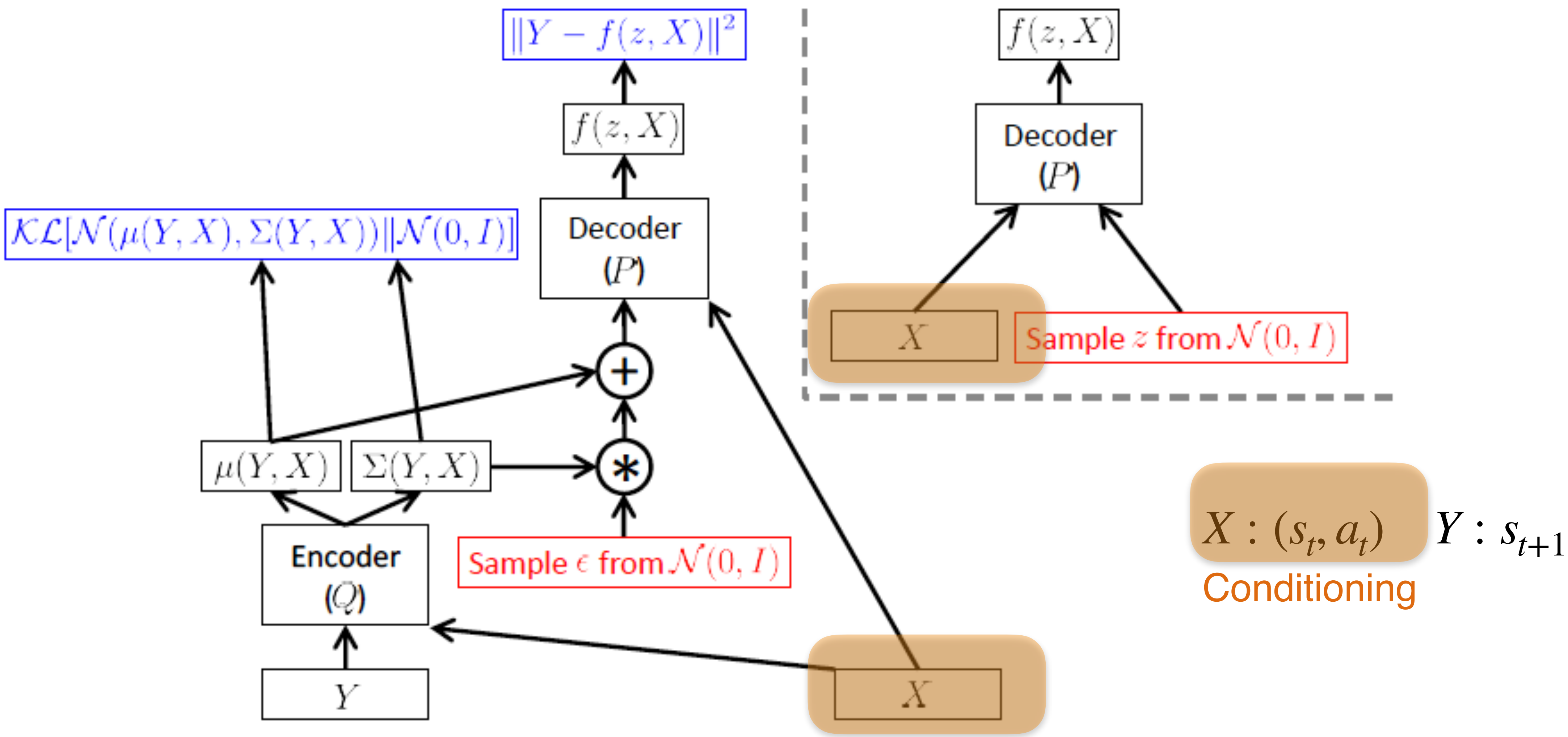




(a) Learned Frey Face manifold (b) Learned MNIST manifold

Auto-Encoding Variational Bayes, *Kingma and Welling*

Conditional VAE



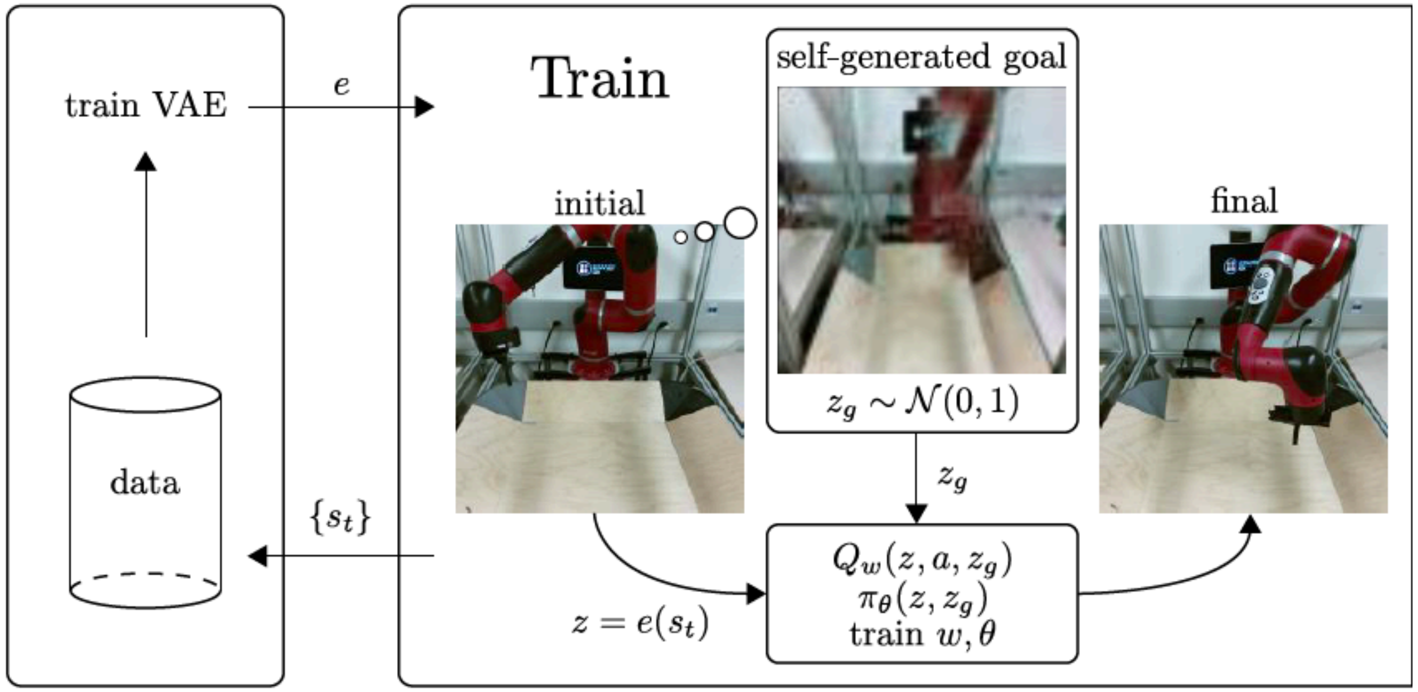
$$\min_{\phi}. \quad D_{KL}(Q(z \mid X, Y) \,||\, P(z \mid \mathcal{D}) = \min_{\phi}. \quad D_{KL}(Q(z \mid X, Y) \mid P(z)) - \mathbb{E}_Q \log P(\mathcal{D} \mid z)$$

Tutotial on variational Autoencoders, Doersch

Visual Reinforcement Learning with Imagined Goals

Ashvin Nair*, Vitchyr Pong*, Murtaza Dalal, Shikhar Bahl, Steven Lin, Sergey Levine
University of California, Berkeley
{anair17,vitchyr,mdalal,shikharbahl,stevenlin598,svlevine}@berkeley.edu

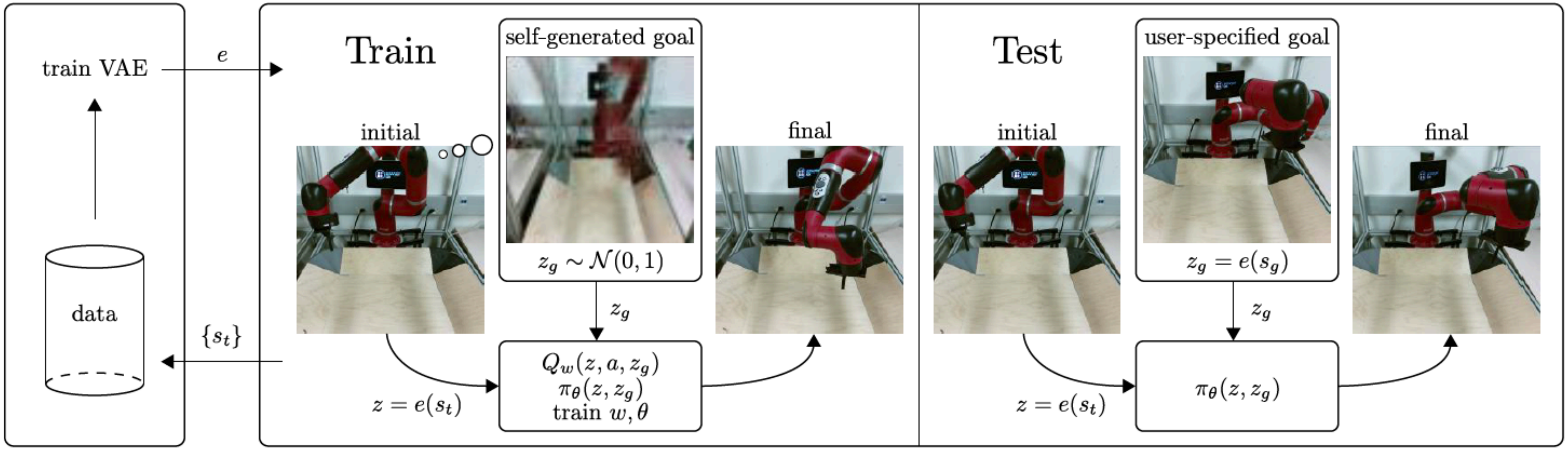
At training time the agent imagines goals to reach by simply sampling codes (vectors) from the latent space.



Visual Reinforcement Learning with Imagined Goals

Ashvin Nair*, Vitchyr Pong*, Murtaza Dalal, Shikhar Bahl, Steven Lin, Sergey Levine
University of California, Berkeley
{anair17,vitchyr,mdalal,shikharbahl,stevenlin598,svlevine}@berkeley.edu

At test time, the human supplies a goal image which is encoded into a latent code by the trained encoder.



Algorithm 1 RIG: Reinforcement learning with imagined goals

Require: VAE encoder q_ϕ, VAE decoder p_ψ, policy π_θ, goal-conditioned value function Q_w.

Collect $\mathcal{D} = \{s^{(i)}\}$ using exploration policy.
Train β-VAE on $\mathcal{D}$ by optimizing (2).
for $n = 0, ..., N-1$ episodes **do**
    Sample latent goal from prior $z_g \sim p(z)$.
    Sample initial state $s_0 \sim E$.
    for $t = 0, ..., H-1$ steps **do**
        Get action $a_t = \pi_\theta(e(s_t), z_g)$ + noise.
        Get next state $s_{t+1} \sim p(\cdot \mid s_t, a_t)$.
        Store (s_t, a_t, s_{t+1}, z_g) into replay buffer $\mathcal{R}$.
        Sample transition $(s, a, s', z_g) \sim \mathcal{R}$.
        Encode $z' = e(s')$.
        (Probability 0.5) replace z_g with $z'_g \sim p(z)$.
        Compute new reward $r = -||z' - z_g||$.
        Minimize (1) using (z, a, z', z_g, r).
    end for
    Fine-tune β-VAE every K episodes on mixture of $\mathcal{D}$ and $\mathcal{R}$.
end for

$$\mathcal{E}(w) = \frac{1}{2}||Q_w(s, a, g) - (r + \gamma \max_{a'} Q_{\bar{w}}(s', a', g))||^2$$

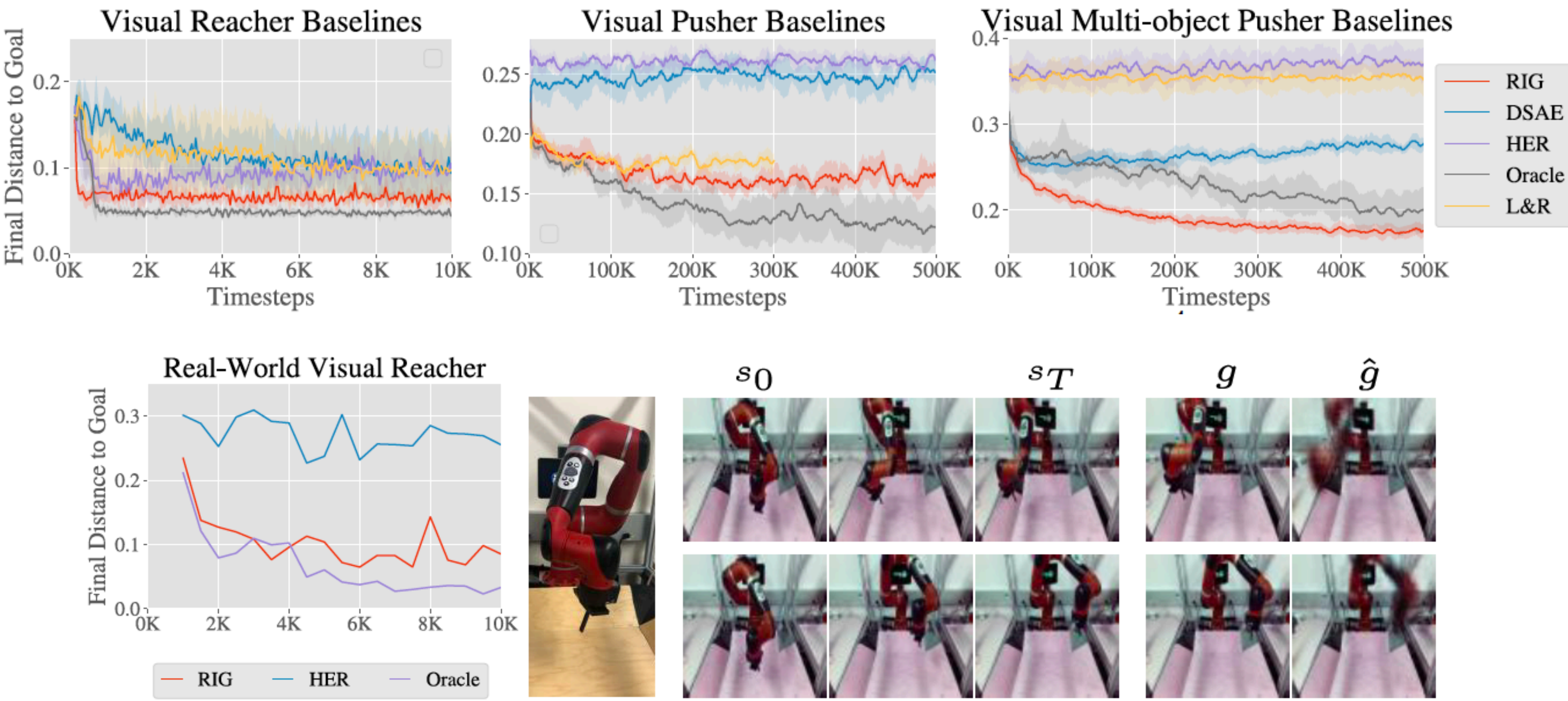


Figure 7: (Left) Our method compared to the HER baseline and oracle on a real-world visual reaching task. (Middle) Our robot setup is pictured. (Right) Test rollouts of our learned policy.

HER here is using L2 over images, that's a terrible (inverse of) reward function