Generative methods in reinforcement learning

Enhanced Experience Replay Generation for Efficient Reinforcement Learning

This paper proposes a approach for pre-training the agentbased on the enhanced GAN data sampling to shorten the train phase.

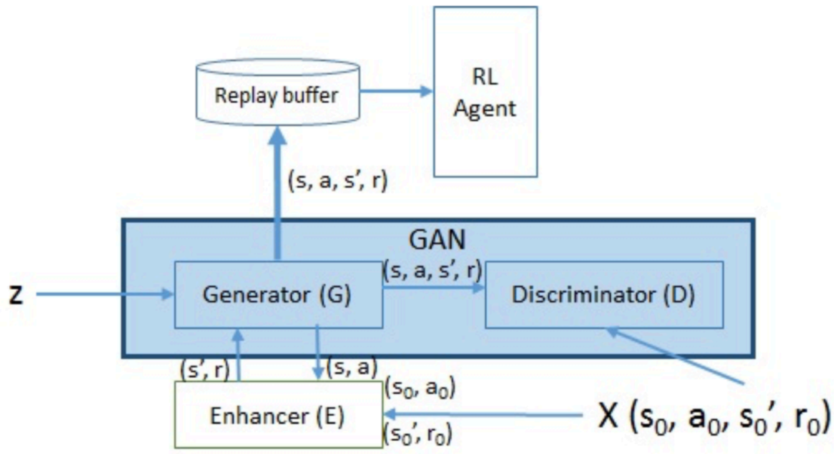


Figure 1: Enhanced GAN structure.

In short, it first collects a small set of data samples using random policy to train the GAN. Then the GAN produces some fake data to pretrain the agent.

Obviously, The Generator produces (s, a) and the Enhancer learns the relation between $(s, a)$and (s', r) and produces (s', r).

Automatic Goal Generation for Reinforcement Learning Agents

It propose a method that allows an agent to automatically discover the range of tasks that it is capable of performing in its environment. That is to say, generate different tasks at the appropriate level of difficulty for the agent.

The mothod can be broken into three parts:

1. Label a set of goals based on whether they are at the appropriate level for e currency policy.

$$GOID_i := \{g : R_{\min} \leq R^g(\pi_i) \leq R_{\max}\} \subseteq \mathcal{G}.$$

R_{min} and R_{max} are hyperparameters and can be interpreted as the minimun and maximun probability of reaching a goal over T steps in the previous training iteration. Then the label $y_g \in \{0, 1\}$ indicates whether $g \in GOID_i$ for all goals g .The put the y_g in the loss function.

$$
\min_D V(D) = \mathbb{E}_{g \sim p_{\text{data}}(g)} \Big[y_g (D(g) - b)^2 + (1 - y_g)(D(g) - a)^2 \Big] + \mathbb{E}_{z \sim p_z(z)} [(D(G(z)) - a)^2]
$$

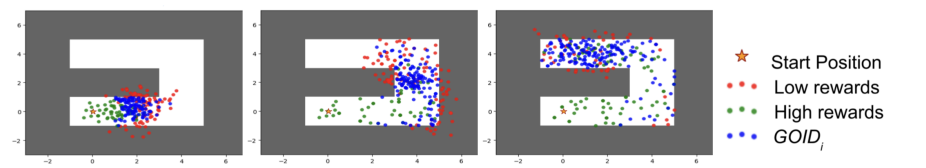
$$
\min_G V(G) = \mathbb{E}_{z \sim p_z(z)} [D(G(z)) - c)^2] \tag{5}
$$

The loss function boosts the generator to produce tasks *not too easy and not too hard.*

2. Use the labels to train the generator to produce new goals.
3. Use these new goals to efficiently train the policy, improving its coverage objective.

Algorithm 1 Generative Goal Learning

Input: Policy π_0
Output: Policy π_N
$(G, D) \leftarrow \texttt{initialize\_GAN}()$
$goals_{\text{old}} \leftarrow \varnothing$
for $i \leftarrow 1$ **to** N **do**
  $z \leftarrow \texttt{sample\_noise}(p_z(\cdot))$
  $goals \leftarrow G(z) \cup \texttt{sample}(goals_{\text{old}})$
  $\pi_i \leftarrow \texttt{update\_policy}(goals, \pi_{i-1})$
  $returns \leftarrow \texttt{evaluate\_policy}(goals, \pi_i)$
  $labels \leftarrow \texttt{label\_goals}(returns)$
  $(G, D) \leftarrow \texttt{train\_GAN}(goals, labels, G, D)$
  $goals_{\text{old}} \leftarrow \texttt{update\_replay}(goals)$
end for



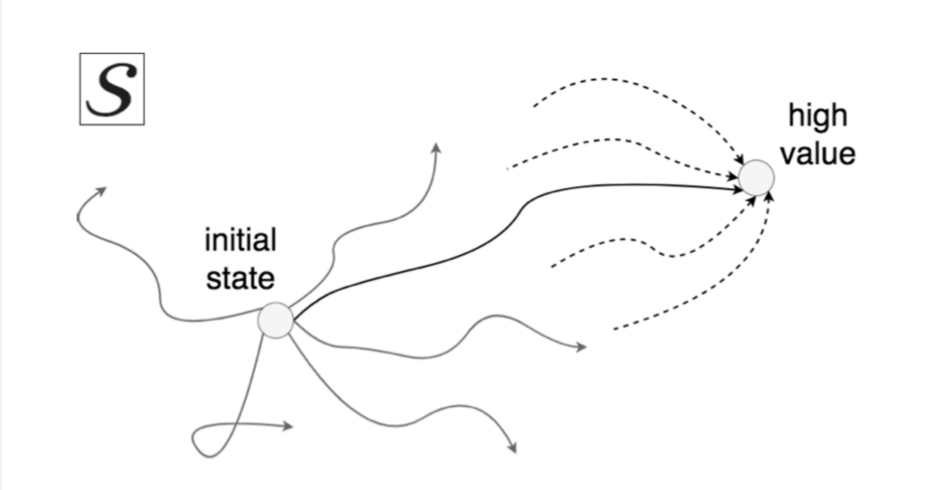
(a) Iteration 5 (b) Iteration 90 (c) Iterartion 350

Figure 3. Goals that, at iterations i, our algorithm trains on - 200 sampled from Goal GAN, 100 from replay. Green goals satisfy $\bar{R}^g(\pi_i) \geq R_{\max}$. Blue ones have appropriate difficulty for the current policy $R_{\min} \leq \bar{R}^g(\pi_i) \leq R_{\max}$. The red ones have $R_{\min} \geq \bar{R}^g(\pi_i)$.

We can see the distribution of generated goals during the training. Green points represent the easy goals, blue points represent the suitable goals and red points mean hard or impossible goals. The learning process shows the agent gradually learns hard tasks.

Recall Traces: Backtracking Models for Efficient Reinforcement Learning

Use a *backtracking* model to predict he precedingtates that terminate at the given high-reward state. Use goal GAN to genetate high value state.



The backtracking model consists of the backward policy $\pi_b = q(_t|s_{t+1})$ and a state genetator $q(s_t|, a_t, s_{t+1})$ .To make the training more stable, we not directly predict the s_t ,but the $\Delta s_t = s_t - s_{t+1}$.

$$q_\phi(\Delta_t, a_t|s_{t+1}) = q(\Delta s_t|a_t, s_{t+1})q(a_t|s_{t+1}).$$

With regard to how to producing high value states, first method is naive. Just pick high value sample from the replay buffer. The second method is based on the goal GAN mention above.

Algorithm 1 Produce High Value States

Require: Critic $V(s)$
Require: D; transformation 'decoder' from g to s
Require: Experience buffer $\mathcal{B}$ with tuples (s_t, a_t, r_t, s_{t+1})
Require: gen_state; boolean whether to generate states
Require: GAN, some generative model trained to model high-value goal states

if gen_state **then**
  $g \sim GAN$
  $D : g \mapsto s$
  Return s
else
  Return $argmax(V(s))\ \forall s \in \mathcal{B}$
end if

How to train

1. Training the Backtracking Model

$$
\begin{aligned}
\mathcal{L}_{\mathcal{B}} = \log q_{\phi}(\tau) &= \log \prod_{t=0}^{T} q(\Delta s_t, a_t | s_{t+1}) \\
&= \sum_{t=0}^{T} \log q(\Delta s_t, a_t | s_{t+1}) \\
&= \sum_{t=0}^{T} \log q(a_t | s_{t+1}) + \log q(\Delta s_t | a_t, s_{t+1}),
\end{aligned}
$$

2. Improving the Policy from the Recall Traces

   RL loss and the imitation loss

$$
\mathcal{L}_{\mathcal{I}} = \sum_{t=0}^{T} \log p(a_t | s_t) = \sum_{t=0}^{T} \log \pi_{\theta}(a_t | s_t),
$$

Algorithm 2 Improve Policy via Backtracking Model

Require: RL algorithm with parameterized policy (i.e. TRPO, Actor-Critic)
Require: Agent policy $\pi_\theta(a|s)$
Require: Backtracking model $B_\phi = q_\phi(\Delta s_t, a_t | s_{t+1})$
Require: Critic $V(s)$
Require: k quantile of best state values used to train backtracking model
Require: N; number of backward trajectories per target state
Require: α, β; forward, backward learning rates
Randomly initialize agent policy parameters θ
Randomly initialize backtracking model parameters ϕ
for $t = 1$ to K **do**
  Execute RL algorithm to produce trajectory τ
  Add trajectory $\tau = (s_1, a_1, r_1, \cdots, s_T, a_T, r_T)$ in $\mathcal{B}$
  Estimate $\nabla_\theta R(\pi_\theta)$ from RL algorithm
  $\theta \leftarrow \theta + \alpha \nabla_\theta R(\pi_\theta)$
  Compute $\mathcal{L}_{\mathcal{B}}$ via Equation 5 using the top $k\%$ of valuable states in $\mathcal{B}$
  $\phi \leftarrow \phi + \beta \nabla_\phi \mathcal{L}_{\mathcal{B}}$
  Algorithm 1 returns a target state s
  Generate N traces $\tilde{\tau}$ for s using $B(s)$
  Compute imitation loss $\mathcal{L}_{\mathcal{I}}$ via Equation 6
  $\theta \leftarrow \theta + \alpha \nabla_\theta \mathcal{L}_{\mathcal{I}}$
  Update sub-goals or high value states.
end for

Exploration

Curiosity-driven Exploration by Self-supervised Prediction

Self-Imitation Learning

Exploiting past good experiences can indirectly drive deep exploration.

Learn to imitate state-action pairs in the replay buffer only when the return in the past episode is greater than the agent's value estimate.

Imitation-learning loss which can be thought of as a clipped advantage: *max(returns - predicted_value, 0)*. The clip is so that if an action actually produces a better-than-expected value, it should be used for training

Learning to Explore with Meta-Policy Gradient

A meta-learning algorithm to directly learn an exploration policy to collect better experience data for DDPG training, instead of using additive noises on actions.

The framework is a teacher-student framework where the exploration policy π_e viewed as the teacher, generates a set of data D_0 at each iteration, and feeds it into a DDPG agent with an actor policyπ (the student) who learns from the data and improves itself.

It trains an another exploration policy using policy gradient. The meta reward is how much it helps the progress of learning the agent.

$$\hat{\mathcal{R}}(D_0) = \hat{R}_{\pi'} - \hat{R}_{\pi},$$

The exploration gradient is

$$\theta^{\pi_e} \leftarrow \theta^{\pi_e} + \eta \hat{\mathcal{R}}(D_0) \sum_{t=1}^{T} \nabla_{\theta^{\pi_e}} \log \pi_e(a_t|s_t).$$

Algorithm 1 Teacher: Learn to Explore

Initialize π_e and π.
Draw D_1 from π to estimate the reward $\hat{R}_\pi$ of π.
Initialize the Replay Buffer $B = D_1$.
for iteration t **do**
  Generate D_0 by executing teacher's policy π_e.
  Update actor policy π to π' using DDPG based on D_0: $\pi' \leftarrow \text{DDPG}(\pi, D_0)$.
  Generate D_1 from π' and estimate the reward of π'. Calculate the meta reward: $\hat{\mathcal{R}}(D_0) = \hat{R}_{\pi'} - \hat{R}_\pi$.
  Update Teacher's Policy π_e with meta policy gradient

$$\theta^{\pi_e} \leftarrow \theta^{\pi_e} + \eta \nabla_{\theta^{\pi_e}} \log \mathcal{P}(D_0|\pi_e) \hat{\mathcal{R}}(D_0)$$

  Add both D_0 and D_1 into the Replay Buffer $B \leftarrow B \bigcup D_0 \bigcup D_1$.
  Update π using DDPG based on Replay Buffer, that is, $\pi \leftarrow \text{DDPG}(\pi,\ B)$. Compute the new $\hat{R}_\pi$.
end for

Meta-Reinforcement Learning of Structured Exploration Strategies

Sparse reward and Data efficiency

Many papers adopt the idea of imitation learning to solve the sparse reward problem. As it is less related to our research, these papers are not listed there.

Hindsight Experience Replay

> *The pivotal idea behind HER is to replay each episode with a different goal than the one the agent was trying to achieve.*

The idea is very easy. Typically, the agent can only gets reward when arriving at the final state, but in HER we sample some additional goals. When the agent arrives at the goals or $|s - g| < \varepsilon$ in continuous space, it can get additional rewards. Then store the new data in the buffer and train the model via off-policy method.

Algorithm 1 Hindsight Experience Replay (HER)

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

Initialize $\mathbb{A}$ ▷ 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 $\mathbb{A}$:
      $a_t \leftarrow \pi_b(s_t||g)$ ▷ || 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 ▷ standard experience replay
    Sample a set of additional goals for replay $G := \mathbb{S}($**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 ▷ 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

Learning by Play- Solving Sparse Reward Task from Scratch

> *The key idea behind our method is that active (learned) scheduling and execution of auxiliary policies allows the agent to efficiently explore its environment.*

This paper gives me a feeling of engineering. It is too complex to figure out which part really helps, although it actually outperforms baselines. The auxiliary reward needs priori knowledge and the task seem to be easy with auxiliary reward.

Inverse Reward Design

This paper proposes a solution to inverse reward design (IRD) which infer the true reward function from a set of given reward functions.

$$P(\widetilde{w}|w^*, \widetilde{M}) \propto \exp\left(\beta\, \mathbb{E}\left[{w^*}^\top \phi(\xi) | \xi \sim \pi(\xi|\widetilde{w}, \widetilde{M})\right]\right)$$

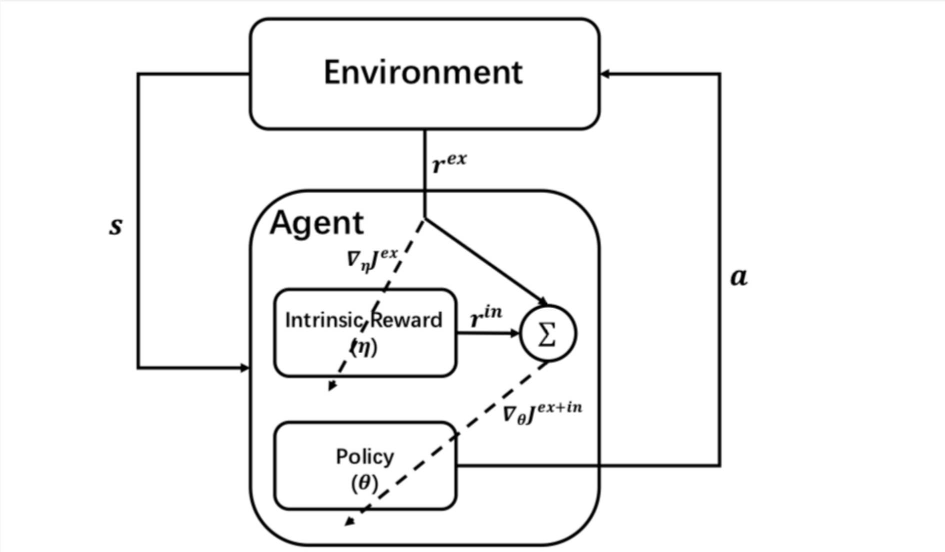
The idea that proxy reward functions are likely to the extent that they incentivize high utility behavior in the training MDP. The P is a distribution on he true utility function.

The distribution means the true utility should be high when the real reward is high. Morever, it tends to penalize no-reward situation. I mean the situation which has less utility. So the model behaves more risk-averse. The agent learns to avoid something unforeseen because it is useless and could brings damage. On the other hand, it also avoids potentially good things as the author mentions in the discussion.

Some methods focus on learning the inintrinsic reward function for the sparse entrinsic reward.

On Learning Intrinsic Rewards for Policy Gradient Methods

In short, the intrinsic reward is trained to optimize the entrinsic reward.



Algorithm 1 LIRPG: Learning Intrinsic Reward for Policy Gradient

Input: step-size parameters α and β
Init: initialize θ and η with random values
repeat
  Sample a trajectory $\mathcal{D} = \{s_0, a_0, s_1, a_1, \cdots\}$ by interacting with the environment using π_θ
  Approximate $\nabla_\theta J^{ex+in}(\theta; \mathcal{D})$ by Equation 4
  Update $\theta' \leftarrow \theta + \alpha \nabla_\theta J^{ex+in}(\theta; \mathcal{D})$
  Approximate $\nabla_{\theta'} J^{ex}(\theta'; \mathcal{D})$ on $\mathcal{D}$ by Equation 11
  Approximate $\nabla_\eta \theta'$ by Equation 10
  Compute $\nabla_\eta J^{ex} = \nabla_{\theta'} J^{ex}(\theta'; \mathcal{D}) \nabla_\eta \theta'$
  Update $\eta' \leftarrow \eta + \beta \nabla_\eta J^{ex}$
until done

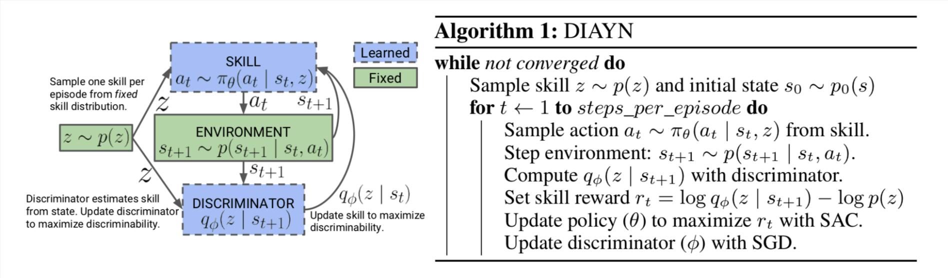
Self-supervised, unsupervised or meta methods in reinforcement learning

Most of papers in this part are related to exploitation and sparse reward.

Curiosity-driven Exploration by Self-supervised Prediction

Diversity is All You Need: Learning Skills Without a Reward Function

The proposed method learns skills by maximizing an information theoretic objective using a maximum entrop policy.



Learn the skill z as the condition in policy $\pi_\theta(a_t|s_t, z)$. Different skills should visit different states, and hence be distinguishable. Skills with high entropy that remain discriminable must explore a part of the state space far away from other skills.

We have three parts to optimize.

1.The mutual information between skills and states.$MI(z, s)$

It means the skills should control which states the agent visits.

2.Minimize the mutual informaiton between skill and action given the state $MI(z, a|s)$

It ensure that states, not actions, are used to distinguish skills.

3.Maximize the $\mathcal{H}([a|s])$

$$\mathcal{F}(\theta) \triangleq MI(s,z) + \mathcal{H}[a \mid s] - MI(a,z \mid s)$$

1 gives intuition on how we optimize it:[3]

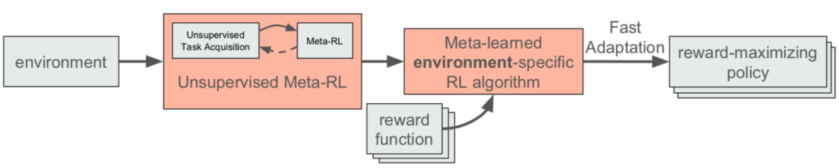
$$\begin{aligned}
\mathcal{F}(\theta) &= MI(s,z) + \mathcal{H}[a \mid s] - MI(a,z \mid s) \\
&= (\mathcal{H}[z] - \mathcal{H}[z \mid s]) + \mathcal{H}[a \mid s] \\
&\quad - (\mathcal{H}[a \mid s] - \mathcal{H}[a \mid s,z]) \\
&= \mathcal{H}[z] - \mathcal{H}[z \mid s] + \mathcal{H}[a \mid s,z]
\end{aligned}$$

$$\begin{aligned}
\mathcal{F}(\theta) &= \mathcal{H}[a \mid s,z] - \mathcal{H}[z \mid s] + \mathcal{H}[z] \\
&= \mathcal{H}[a \mid s,z] + \mathbb{E}[\log p(z \mid s)] - \mathbb{E}[\log p(z)] \\
&\geq \mathcal{H}[a \mid s,z] + \mathbb{E}[\log q_\phi(z \mid s) - \log p(z)] \triangleq \mathcal{G}(\theta,\phi)
\end{aligned}$$

So the reward function can be written as:

$$r_z(s,a) \triangleq \log q_\phi(z \mid s) - \log p(z)$$

Unsupervised Meta-Learning for Reinforcement Learning



Algorithm 1: Unsupervised Meta-Reinforcement Learning Pseudocode

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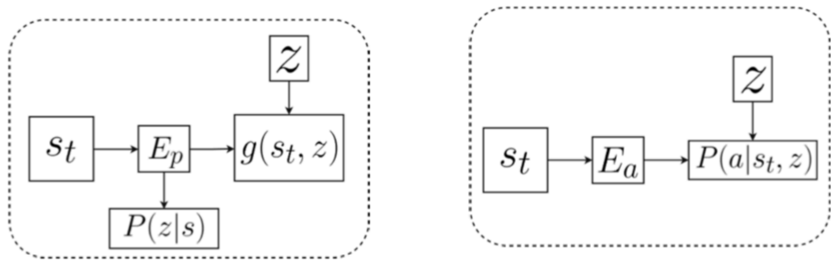
Data: $\mathcal{M} \setminus R$, an MDP without a reward function
Result: a learning algorithm $f : \mathcal{D} \to \pi$
Initialize $\mathcal{D} = \emptyset$
$D_\phi \leftarrow$ DIAYN() or $D_\phi \leftarrow random$
while *not converged* **do**
  Sample latent task variables $z \sim p(z)$
  Extract corresponding task reward functions $r_z(s)$ using $\mathcal{D}_\phi(z|s)$
  update f using MAML with reward $r_z(s)$

Use DIAYN to learn a policy and discriminator. Sample tasks by generating samples $z \sim p(z)$ and using the conrrespondnig task reward $r_z(s) = \log(D_\phi(z|s))$

Imitating Latent Policies from Observation

This paper proposed a imitation learning method to infer latent policies from expert observations. It is a two-stage model.



(a) Latent Policy Net (b) Action Remapping Net

Step 1: learning latent policies

From the expert observation $\{s_1, \dots, s_t\}$ learn the latent policy $P(z|s_t)$ by fitting the s_t and s_{t+1} .

$$\mathcal{L}_{min} = min\|\Delta_t - g(s_t, z)\|^2, \Delta_t = s_{t+1} - s_t$$

$$\mathcal{L}_{exp} = \|s_{t+1} - \hat{s}_{t+1}\|^2, \hat{s}_{t+1} = \sum_z P(z|s_t)g(s_t|z)$$

$$\mathcal{L} = \mathcal{L}_{min} + \mathcal{L}_{exp}$$

Step2 :Action remapping

Learn a mapping from the latent space to the true sction space $P(a|z, s_t)$. The agent randomly selects a_t then we can get (S_t, A_t, S_{t+1}). Select the z_t which causes the s_{t+1} by the learned model from the Step 1. Therefore, the z_t is corresponding to the evnironment action a_t.

Step 2: Action remapping
Observe state s_0
for $t \leftarrow 0 \dots$ *#Interactions* **do**
    Choose latent action $z_t \leftarrow \arg\max_z P_\omega(z|s_t)$
    Take ϵ-greedy action $a_t \leftarrow \arg\max_a P_\xi(a|z_t, s_t)$
    Observe state s_{t+1}
    Infer closest latent action $\hat{z} = \arg\min_z \|E_p(s_{t+1}) - E_p(g(s_t, z))\|^2$
    $\xi \leftarrow \xi + \nabla_\xi \log \frac{P(a_t|\hat{z}, s_t)}{\sum_a P(a|\hat{z}, s_t)}$

Credit assignment for multi-agent reinforcment learning