Learning to Assist Humans without Inferring Rewards

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Abstract

Assistive agents should make humans' lives easier. Classically, such assistance is studied through the lens of inverse reinforcement learning, where an assistive agent (e.g., a chatbot, a robot) infers a human's intention and then selects actions to help the human reach that goal. This approach requires inferring intentions, which can be difficult in high-dimensional settings. We build upon prior work that studies assistance through the lens of empowerment: an assistive agent aims to maximize the influence of the human's actions such that they exert a greater control over the environmental outcomes and can solve tasks in fewer steps. We lift the major limitation of prior work in this area—scalability to high-dimensional settings—with contrastive successor representations. We formally prove that these representations estimate a similar notion of empowerment to that studied by prior work and provide a ready-made mechanism for optimizing it. Empirically, our proposed method outperforms prior methods on synthetic benchmarks, and scales to Overcooked, a cooperative game setting. Theoretically, our work connects ideas from information theory, neuroscience, and reinforcement learning, and charts a path for representations to play a critical role in solving assistive problems.

1 Introduction

AI agents deployed in the real world should be helpful to humans. When we know the utility function of the humans an agent could interact with, we can directly train assistive agents through reinforcement learning with the known human objective as the agent's reward. In practice, agents rarely have direct access to a scalar reward corresponding to human preferences (if such a consistent model even exists) (Casper et al., 2023), and must infer them from human behavior (Hadfield-Menell et al., 2016; 2017). This inference can be challenging, as humans may act suboptimally with respect to their stated goals, not know their goals, or have changing preferences (Carroll et al., 2021). Optimizing a misspecified reward function can have poor consequences (Turner et al., 2023).

An alternative paradigm for assistance is to train agents that are *intrinsically* motivated to assist humans, rather than directly optimizing a model of their preferences. An analogy can be drawn to a parent raising a child. A good parent will empower the child to make impactful decisions and flourish, rather than proscribing an "optimal" outcome for the child. Likewise, AI agents might seek to *empower* the human agents they interact with, maximizing their capacity to change the environment (Du et al., 2020). In practice, concrete notions of empowerment can be difficult to optimize as an objective, requiring extensive modeling assumptions that don't scale well to the high-dimensional settings deep reinforcement learning agents are deployed in.

What is a good intrinsic objective for assisting humans that doesn't require these assumptions? We propose a notion of assistance based on maximizing the influence of the human's actions on the environment. This approach only requires one structural assumption: the AI agent is interacting with an environment where there is a notion of actions taken by the human agent—a more general setting than the case where we model the human actions as the outcome of some optimization procedure, as in IRL (Russell, 1998; Arora & Doshi, 2021) or PbRL (Wirth et al., 2017).

Prior work has studied many effective objectives for empowerment. For instance, Du et al. (2020) approximates human empowerment as the variance in the final states of random rollouts. Despite excellent results in certain settings, this approach can be challenging to scale to higher dimensional settings, and does not necessarily enable human users to achieve the goals the want to achieve. By contrast, our approach exclusively empowers the human with respect to the distribution of (useful) behaviors induced by their current policy, and can be implemented through a simple objective derived from contrastive successor features, which can then be optimized with scalable deep reinforcement learning (Fig. 1). We provide a theoretical framework connecting our

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Our code is available at `https://anonymous.4open.science/r/esr-7E94`.

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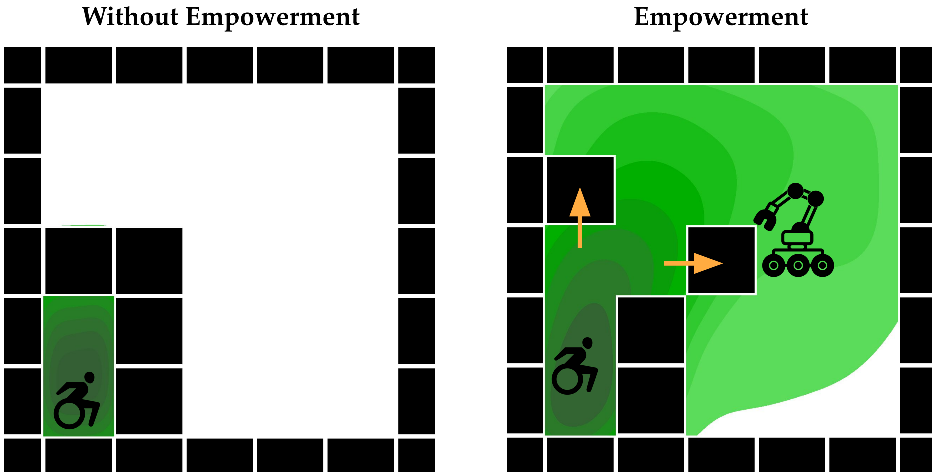


Figure 1: We propose an algorithm training assistive agents to empower human users—the assistant should take actions that enable human users to visit a wide range of future states, and the human's actions should exert a high degree of influence over the future outcomes. Our algorithm scales to high-dimensional settings, opening the door to building assistive agents that need not directly reason about human intentions.

objective to prior work on empowerment and goal inference, and empirically show that agents trained with this objective can assist humans in the Overcooked environment (Carroll et al., 2020) as well as the obstacle gridworld assistance benchmark proposed by Du et al. (2020).

Our core contribution is a novel objective for training agents that are intrinsically motivated to assist humans without requiring a model of the human's reward function. Our objective maximizes the influence of the human's actions on the environment, and, unlike past approaches for assistance without reward inference, is based on a scalable model-free objective that can be derived from learned successor features that encode which states the human is likely to want to reach given their current action. Our objective empowers the human to reach the desired states, not all states, without assuming a human model. We analyze this objective in terms of empowerment and goal inference, drawing novel mathematical connections between time-series representations, decision-making, and assistance. We empirically show that agents trained with our objective can assist humans in two benchmarks proposed by past work: the Overcooked environment (Carroll et al., 2020) and an obstacle-avoidance gridworld (Du et al., 2020).

2 Related Work

Our approach broadly connects ideas from contrastive contrastive representation learning and intrinsic motivation to the problem of assisting humans.

Assistive Agents. There are two lines of past work on assistive agents that are most relevant.

The first line of work focuses on the setting of an assistance game (Hadfield-Menell et al., 2016), where a robot (AI) agent tries to optimize a human reward of which it is initially unaware. Practically, inverse reinforcement learning (IRL) can be used in such a setting to infer the human's reward function and assist the human in achieving their goals (Hadfield-Menell et al., 2017). The key challenge with this approach is that it requires modeling the human's reward function. This can be difficult in practice, especially if the human's behavior is not well-modeled by the reward architecture. Slightly mispecified reward functions can lead to catastrophic outcomes (i.e., directly harmful behavior in the assistance context) (Pan et al., 2022; Tien et al., 2023; Laidlaw et al., 2024). By contrast, our approach does not require modeling the human's reward function.

The second line of work focuses on empowerment-like objectives for assistance and shared autonomy. Empowerment generally refers to a measure of an agent's ability to influence the environment (Salge et al., 2013; de Abril & Kanai, 2018). In the context of assistance, Du et al. (2020) show one such approximation of empowerment (AvE) can be approximated in simple environments through random rollouts to assist humans. Meanwhile, empowerment-like objectives have been used in shared autonomy settings to assist humans with teleoperation (Chen et al., 2022) and general assistive interfaces (Reddy et al., 2022). A key limitation of these approaches for general assistance is they only model empowerment over one time step. Our approach enables a more scalable notion of empowerment that can be computed over multiple time steps.

Intrinsic Motivation. Intrinsic motivation broadly refers to agents that accomplish behaviors in the absence of an externally-specified reward or task (Barto, 2013). Common applications of intrinsic motivation in single-agent reinforcement learning include exploration and skill discovery (Aubret et al., 2019; Eysenbach et al., 2018; Burda et al., 2018), empowerment (de Abril & Kanai, 2018; Salge et al., 2013), and surprise minimization (Friston, 2010; Berseth et al., 2021; de Abril & Kanai, 2018). When applied to settings with humans, these objectives may lead to antisocial behavior (Turner et al., 2023). Our approach applies intrinsic motivation to the setting of assisting humans, where the agent's goal is an empowerment objective—to maximize the human's ability to change the environment.

Information-theoretic Decision Making. Information-theoretic approaches have seen broad applicability across unsupervised reinforcement learning (Poole et al., 2019; de Abril & Kanai, 2018; Aubret et al., 2019). These methods have been applied to goal-reaching (Choi et al., 2021), skill discovery (Mohamed & Rezende, 2015; Jung et al., 2011; Eysenbach et al., 2018; Laskin et al., 2022; Park et al., 2021), and exploration (Burda et al., 2018; Still & Precup, 2012; Nikolov et al., 2019). In the context of assisting humans, information-theoretic methods have primarily been used to reason about the human's goals or rewards (Biyik et al., 2021; Myers et al., 2022; Houlsby et al., 2011).

Our approach is made possible by advances in contrastive representation learning for efficient estimation of the mutual information of sequence data (van den Oord et al., 2019). While these methods have been widely used for representation learning (Chen et al., 2020; Wu et al., 2018) and reinforcement learning (Laskin et al., 2020; Eysenbach et al., 2022; Dayan, 1993; Momennejad et al., 2017), to the best of our knowledge prior work has not used these contrastive techniques for learning assistive agents.

3 The Information Geometry of Empowerment

We will first state a general notion of an assistive setting, then show how an empowerment objective based on learned successor representations can be used to assist humans without making assumptions about the human following an underlying reward function. In Section 5, we provide empirical evidence supporting these claims.

3.1 Preliminaries

Formally, we adapt the notation of Hadfield-Menell et al. (2016), and assume a "robot" (**R**) and "human" (**H**) policy are training together in an MDP $M = (\mathcal{S}, \mathcal{A}_{\mathbf{H}}, \mathcal{A}_{\mathbf{R}}, R, P, \gamma)$. The observations s consistent of the joint states of the robot and the human; we do not have separate observations for the human and robot. At any state $s \in \mathcal{S}$, the robot policy selects actions distributed according to $\pi_R(a^{\mathbf{R}} \mid s)$ for $a^{\mathbf{R}} \in \mathcal{A}_{\mathbf{R}}$ and the human selects actions from $\pi_H(a^{\mathbf{H}} \mid s)$ for $a^{\mathbf{H}} \in \mathcal{A}_{\mathbf{H}}$. The transition dynamics are defined by a distribution $P(s' \mid s, a^{\mathbf{H}}, a^{\mathbf{R}})$ over the next state $s' \in \mathcal{S}$ given the current state $s \in \mathcal{S}$ and actions $a^{\mathbf{H}} \in \mathcal{A}_{\mathbf{H}}$ and $a^{\mathbf{R}} \in \mathcal{A}_{\mathbf{R}}$, as well as an initial state distribution $P(s_0)$. For notational convenience, we will additionally define random variables $\mathfrak{s}_t$ to represent the state at time t, and $\mathfrak{a}^{\mathbf{R}}_t \sim \pi_R(\bullet \mid \mathfrak{s}_t)$ and $\mathfrak{a}^{\mathbf{H}}_t \sim \pi_H(\bullet \mid \mathfrak{s}_t)$ to represent the human and robot actions at time t, respectively.

Empowerment. Our work builds on a long line of prior methods that use information theoretic objectives for RL. Specifically, we adopt *empowerment* as an objective for training an assistive agent (Du et al., 2020; Salge et al., 2014; Klyubin et al., 2005). This section provides the mathematical foundations for empowerment, as developed in prior work. Our work will build on the prior work by (1) providing an information geometric interpretation of what empowerment does (Sec. 3.3) and (2) providing a scalable algorithm for estimating and optimizing empowerment, going well beyond the gridworlds studied in prior work.

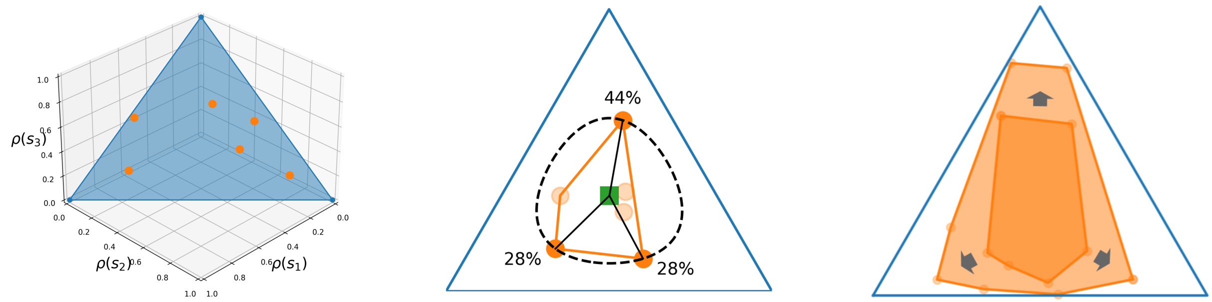
The idea behind empowerment is to think about the changes that an agent can effect on a world; an agent is more empowered if it can effect a larger degree of change over future outcomes. Following prior work (Choi et al., 2021; Klyubin et al., 2005; Salge et al., 2014), we measure empowerment by looking at how much the actions taken *now* affect outcomes *in the future*. An agent with a high degree of empowerment exerts a high degree of control of the future states by simply changing the actions taken now. Like prior work, we measure this degree of control through the mutual information $I(\mathfrak{s}^+; a^{\mathbf{H}})$ between the current action $a^{\mathbf{H}}$ and the future states $\mathfrak{s}^+$. Note that these future states might occur many time steps into the future.

Empowerment depends on several factors: the environment dynamics, the choice of future actions, the current state, and other agents in the environment. Different problem settings involve maximizing empowerment using these different factors. In this work, we study the setting where a "human" agent and a "robot" agent collaborate in an environment; the robot will aim to maximize the empowerment of the human. This problem setting was introduced in prior work (Du et al., 2020). Compared with other mathematical frameworks for learning assistive agents (Reddy et al., 2018), framing the problem in terms of empowerment means that the assistive agent need not infer the human's underlying intention, an inference problem that is typically challenging (Ratliff et al., 2006; Abbeel & Ng, 2004).

Formally, we define the *empowerment* $\mathcal{E}(\pi_H, \pi_R)$ as the mutual information between the human's actions and the future states $\mathfrak{s}^+$ while interacting with the robot:

$$\mathcal{E}(\pi_H, \pi_R) = \mathbb{E}\Big[\sum_{t=0}^{\infty} \gamma^t I(\mathfrak{a}^{\mathbf{H}}_t; \mathfrak{s}^+ \mid \mathfrak{s}_t)\Big], \tag{1}$$

where $\mathfrak{s}^+$ is a future state sampled $K \sim \mathrm{Geom}(1-\gamma)$



(a) State marginal polytope (b) Mutual information (c) Maximizing empowerment

Figure 2: **The Information Geometry of Empowerment**, illustrating the analysis in Sec. 3.3. *(Left)* For a given controlled Markov process, each policy induces a distribution over states. In a 3-state MDP, we can represent each policy as a vector lying on the 2-dimensional probability simplex. We refer to the set of all possible state distributions as the *state marginal polytope*. *(Center)* Mutual information corresponds to the distance between the center of the polytope and the vertices that are maximally far away. *(Right)* Empowerment corresponds to maximizing the size of this polytope. For example, when an assistive agent moves an obstacle out of a human user's way, the human user can spend more time at desired state.

steps into the future under the behavior policies π_H, π_R, and where the mutual information is defined as

$$I(a_t^{\mathbf{H}}; \mathfrak{s}^+ \mid s_t) \triangleq \mathbb{E}_{s_t, s_{t+k}, a_t^{\mathbf{H}}, a_t^{\mathbf{R}}} \left[\log \frac{p(\mathfrak{s}_{t+K} = s_{t+k} \mid \mathfrak{s}_t = s_t, \mathfrak{a}_t^{\mathbf{H}} = a_t)}{p(\mathfrak{s}_{t+K} = s_{t+k} \mid \mathfrak{s}_t = s_t)}\right].$$

Note that this objective resembles an RL objective: we do not just want to maximize this objective greedily at each time step, but rather want the assistive agents to take actions now that help the human agent reach states where it will have high empowerment in the future.

3.2 Assistive Agents Maximize Coverage

Intuitively, the assistive agent should aim to maximize the size of this set of possible measures. We can formalize this intuition by employing a result from Eysenbach et al. (2021, Lemma 6.2), which says that a human maximizing mutual information will only select those skills z that are maximally far away from the prior.

Lemma 1 (Lemma 6.2 from Eysenbach et al. (2021))**.** *Let $\pi_H(z)$ be the human's skill distribution that maximizes mutual information. Then we have*

$$\pi_H^*(z) > 0 \implies D_{KL}\big(\rho(s \mid z) \,\|\, \rho(s)\big) = \max_{z^*} D_{KL}\big(\rho(s \mid z^*) \,\|\, \rho(s)\big). \quad (2)$$

Noting that the mutual information is the expected value of this KL divergence over $\pi_H^*(z)$, we have

$$I^{\pi_H^*}(\mathfrak{s}^+; z) = \max_{z^*} D_{KL}\big(\rho(s \mid z^*) \| \rho(s)\big) \triangleq d_{max}. \quad (3)$$

Thus, we can think about mutual information maximization as finding the set of skills with the maximal coverage – where skills are maximally far away from their center.

Now, by extension, a robot assistant that is maximizing this mutual information also aims to increase the size of this set:

$$\max_{\pi_R} I^{\pi_R, \pi_H^*}(\mathfrak{s}^+; z) = \max_{\pi_R} d_{\max}. \quad (4)$$

In other words, an agent maximizing the empowerment of the human will aim to increase the support of goals the human can reach conditioned on their intention (Fig. 2).

3.3 The Information Geometry of Empowerment

To build on this intuition, we will show that in the special case where the human is well-modeled as optimizing a reward function, we can relate empowerment maximization to reward maximization. Since a key advantage of empowerment is that it does not necessarily require this assumption to be a meaningful assistance objective, we can view our objective as a generalization of the assistance problem beyond the CIRL setting (Hadfield-Menell et al., 2016). In particular, we will show that under certain assumptions maximizing empowerment corresponds to provably increasing their expected rewards.

Lemma 2. *Assume that a human has learned skills $\pi(a \mid s, z)$ by maximizing mutual information $I(\mathfrak{s}^+; z)$ and adapts to a reward function by minimizing the regularized regret:*

$$\min_{\rho^* \in \mathcal{C}^{\pi_R}} \max_{\rho^+ \in \mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)] + D_{KL}\big(\rho^*(s) \| \rho(s)\big). \quad (5)$$

We assume that the human chooses the prior $\rho(s)$ that minimizes this regret for the worst-case choice of reward function (i.e., the minimax optimal prior). An assistive agent that maximizes $I^{\pi_R}(\mathfrak{s}^+; z)$ minimizes the worst-case (regularized) regret incurred by the human.

Letting $\pi_R^* \in \arg\max_{\pi_R} I^{\pi_R}(\mathfrak{s}^+; z)$, we have

$$\pi_R^* \in \arg\min_{\pi_R}\Bigg(\min_{\rho(s)\in\mathcal{C}^{\pi_R}} \max_{r(s)} \min_{\rho^*\in\mathcal{C}^{\pi_R}} \max_{\rho^+\in\mathcal{C}^{\pi_R}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)] + D_{KL}(\rho^*(s)\|\rho(s))\Bigg). \quad (6)$$

The proof is in Appendix B. To the best of our knowledge, this theoretical result provides the first formal link between empowerment maximization and reward maximization. This motivates us to develop a scalable algorithm for empowerment maximization, which we introduce in the following section.

4 Estimating and Maximizing Empowerment with Contrastive Representations

Directly computing equation 1 would require access to the human policy, which we don't have. Therefore, we want a tractable estimation that still performs well in large environments which are more difficult to model due to the exponentially increasing set of possible future states. To better-estimate empowerment, we learn contrastive representations that encode information about which future states are likely to be reached from the current state. These contrastive representations learn to model mutual information between the current state, action, and future state, which we then use to compute the empowerment objective.

4.1 Estimating Empowerment

To estimate this empowerment objective, we need a way of learning the probability ratio inside the expectation. Prior methods such as Du et al. (2020) and Salge et al. (2014) rollout possible future states and compute a measure of their variance as a proxy for empowerment, however this doesn't scale when the environment becomes complex. Other methods learn a dynamics model, which also doesn't scale when dynamics become challenging to model (Jung et al., 2011). Modeling these probabilities directly is challenging in settings with high-dimensional states, so we opt for an indirect approach. Specifically, we will learn representations that encode two probability ratios. Then, we will be able to compute the desired probability ratio by combining these other probability ratios.

Our method will learn three representations:

1. $\phi(s, a^{\mathbf{R}}, a^{\mathbf{H}})$ – This representation can be understood as a sort of latent-space model, predicting the future representation given the current state s and the human's current action $a^{\mathbf{H}}$ as well as the robot's current action $a^{\mathbf{R}}$.
2. $\phi'(s, a^{\mathbf{R}})$ – This representation can be understood as an uncontrolled model, predicting the representation of a future state without reference to the current human action $a^{\mathbf{H}}$. This representation is analogous to a value function.
3. $\psi(g)$ – This is a representation of a future state.

We will learn these three representations with two contrastive losses, one that aligns $\phi(s, a^{\mathbf{H}}) \leftrightarrow \psi(g)$ and one that aligns $\phi'(s) \leftrightarrow \psi(g)$

$$\max_{\phi,\phi',\psi} \mathbb{E}_{\{(s_i,a_i,s_i')\sim p(\mathfrak{s}_t,\mathfrak{a}_t^{\mathbf{H}},\mathfrak{s}_{t+k})\}_{i=1}^N} \Big[\mathcal{L}_{\mathsf{c}}(\{\phi(s_i,a_i)\},\{\psi(s_j')\}) + \mathcal{L}_{\mathsf{c}}(\{\phi'(s_i)\},\{\psi(s_j')\})\Big], \quad (7)$$

where the contrastive loss $\mathcal{L}_{\mathsf{c}}$ is the symmetrized infoNCE objective (van den Oord et al., 2019):

$$\mathcal{L}_{\mathsf{c}}(\{x_i\},\{y_j\}) \triangleq \sum_{i=1}^N \left[\log\left(\frac{e^{x_i^T y_i}}{\sum_{j=1}^N e^{x_i^T y_j}}\right) + \log\left(\frac{e^{x_i^T y_i}}{\sum_{j=1}^N e^{x_j^T y_i}}\right)\right]. \quad (8)$$

We have colored the index j for clarity. At convergence, these representations encode two probabilities ratios (Poole et al., 2019), which we will ultimately be able to use to estimate empowerment (Eq. 1):

$$\phi(s, a^{\mathbf{R}}, a^{\mathbf{H}})^T\psi(g) = \log\left[\frac{p(\mathfrak{s}_{t+K}=g \mid \mathfrak{s}_t=s, \mathfrak{a}_t^{\mathbf{H}}=a)}{C_1 p(\mathfrak{s}_{t+K}=g)}\right] \quad (9)$$

$$\phi'(s, a^{\mathbf{R}})^T\psi(g) = \log\left[\frac{p(\mathfrak{s}_{t+K}=s_{t+k} \mid \mathfrak{s}_t=s_t)}{C_2 p(\mathfrak{s}_{t+K}=g)}\right]. \quad (10)$$

Note that our definition of empowerment (Eq. 1) is defined in terms of similar probability ratios. The constants C_1 and C_2 will mean that our estimate of empowerment may be off by an additive constant, but that constant will not affect the solution to the empowerment maximization problem.

4.2 Estimating Empowerment with Learned Representations

To estimate empowerment, we will look at the difference between these two inner products:

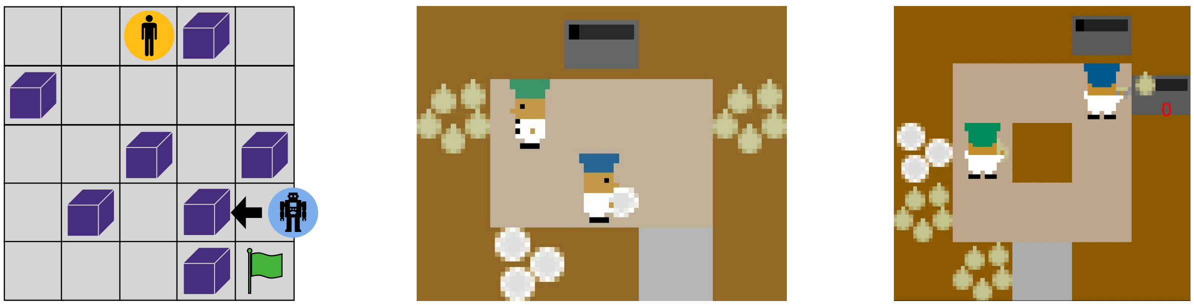
$$\begin{aligned}
&\phi(s_{t+K}, a^{\mathbf{R}}, a^{\mathbf{H}})^T\psi(g) - \phi(s_{t+K}, a^{\mathbf{R}})^T\psi(g) \\
&= \log p(s_{t+K} \mid s, a^{\mathbf{H}}) - \log C_1 - \cancel{\log p(s_{t+K})} \\
&\qquad - \log p(s_{t+K} \mid s) + \log C_2 + \cancel{\log p(s_{t+K})} \\
&= \log \frac{p(s_{t+K} \mid s, a^{\mathbf{H}})}{p(s_{t+K} \mid s)} + \log\frac{C_2}{C_1}.
\end{aligned}$$

Note that the expected value of the first term is the *conditional* mutual information $I(s_{t+K}; a^{\mathbf{H}} \mid s)$. Our empowerment objective corresponds to averaging this mutual information across all the visited states. In other words, our objective corresponds to an RL problem, where empowerment corresponds to the expected discounted sum of these log ratios:

$$\begin{aligned}
\mathcal{E}(\pi_H, \pi_R) &= \mathbb{E}_{\pi_H,\pi_R}\left[\textstyle\sum_{t=0}^\infty \gamma^t I(a_t^H; s_t \mid s_t)\right] \\
&\approx \mathbb{E}_{\pi_H,\pi_R}\left[\textstyle\sum_{t=0}^\infty \gamma^t \big(\phi(s_t, a^{\mathbf{R}}, a^{\mathbf{H}}) - \phi(s_t, a^{\mathbf{R}})\big)^T\psi(g) - \log\frac{C_2}{C_1}\right].
\end{aligned}$$

Algorithm 1: Empowerment via Successor Representations (ESR)

Input: Human policy $\pi_H(a \mid s)$
Randomly initialize assistive agent policy $\pi_R(a \mid s)$, and representations $\phi(s, a^{\mathbf{R}}, a^{\mathbf{H}})$, $\psi(s, a^T)$, and $\psi(g)$.
Initialize replay buffer $\mathcal{B}$.
while not converged **do**
    Collect a trajectory of experience with human policy and assistive agent policy, store in replay buffer $\mathcal{B}$.
    Update representations $\phi(s, a^{\mathbf{R}}, a^{\mathbf{H}})$, $\psi(s, a^T)$, and $\psi(g)$ with the contrastive losses in Eq. (7).
    Update $\pi_R(a \mid s)$ with RL using reward function $r(s, a^{\mathbf{R}}, a^{\mathbf{H}}) = (\phi(s, a^{\mathbf{R}}, a^{\mathbf{H}}) - \phi'(s, a^{\mathbf{R}}))^T \psi(g)$.
Return: Assistive policy $\pi_R(a \mid s)$.



(a) Obstacle Gridworld (b) Cramped Room (c) Coordination Ring

Figure 3: The modified environment from Du et al. (2020) scaled to $N = 7$ blocks (left), and the two layouts of the Overcooked environment (Carroll et al., 2020) (middle and right).

The approximation above comes from function approximation in learning the Bayes optimal representations. Again, note that the constants C_1 and C_2 do not change the optimization problem. Thus, to maximize empowerment we will apply RL to the assistive agent $\pi_R(a \mid s)$ using a reward function

$$r(s, a^{\mathbf{R}}) = (\phi(s_t, a^{\mathbf{R}}, a^{\mathbf{H}}) - \phi(s_t, a^{\mathbf{R}}))^T \psi(g). \quad (11)$$

4.3 Algorithm Summary

We propose an actor-critic method for learning the assistive agent. Our method will alternative between updating these contrastive representations and using them to estimate a reward function (Eq. 11 that is optimized via RL. We summarize the algorithm in Alg. 1. In practice, we use SAC (Haarnoja et al., 2018) as our RL algorithm. In our experiments, we will also study the setting where the human user updates their policy alongside the assistive agent.

5 Experiments

We hope to answer two questions with our experiments: (1) Does our approach enable assistance in standard cooperation benchmarks? (2) Does our approach scale to harder benchmarks where prior methods fail?

Our experiments will use two benchmarks designed by prior work to study assistance: the obstacle gridworld (Du et al., 2020) and Overcooked (Carroll et al., 2020). Our main **baseline** will be AvE (Du et al., 2020), a prior empowerment-based method. Our conjecture is that both methods will perform well on the lower-dimensional gridworld task, and that our method will scale more gradefully to the higher dimensional Overcooked environment. We will also compare against a naïve baseline where the assistive agent acts randomly.

5.1 Do contrastive successor representations effectively estimate empowerment?

We test our approach in the assistance benchmark suggested in Du et al. (2020). The human (orange) is tasked with reaching a goal state (green) while avoiding the obstacles (purple). The AI assistant can move blocks one step at a time in any direction (Du et al., 2020). While the original benchmark used $N = 2$ obstacles, we will additionally evaluate on harder versions of this task with $N = 5, 7, 10$ obstacles. We show results in Fig. 4. On the easiest task, both our method and AvE achieve similar asymptotic reward, though our method learns more slowly than AvE. However, on the tasks with moderate and high degrees of complexity, our approach (ESR) achieves significantly higher rewards than AvE, which performs worse than a random controller. These experiments support our claim that contrastive successor representations provide an effective means for estimating empowerment, and hint that ESR might be well suited for solving higher dimensional tasks.

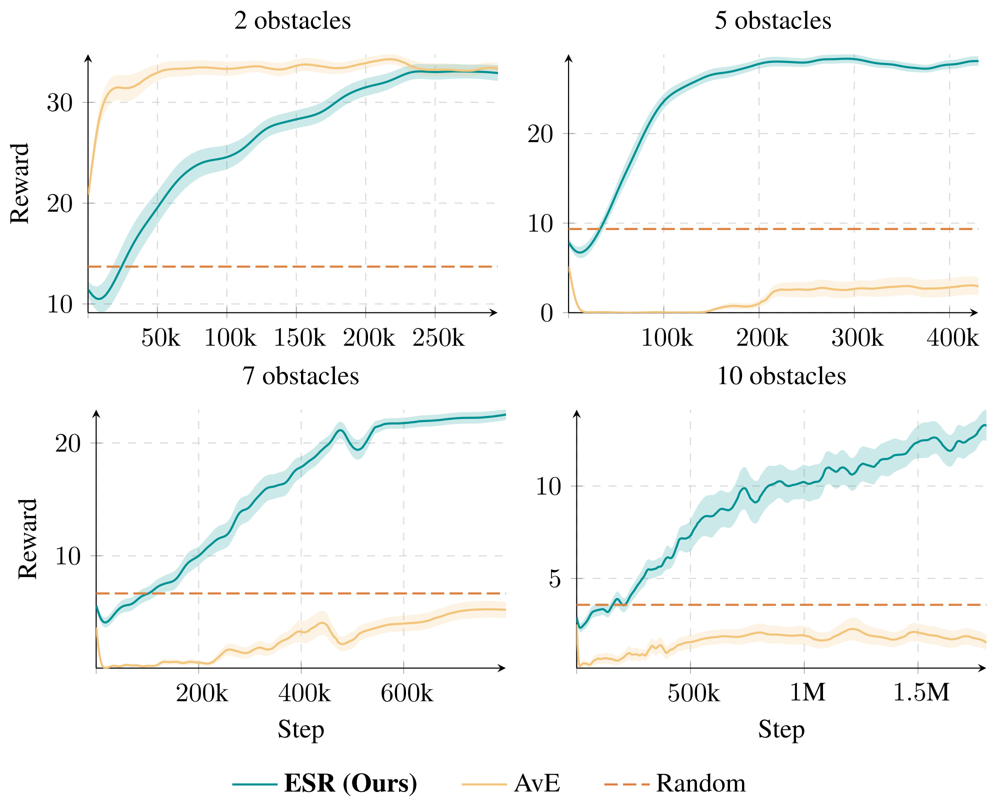


Figure 4: We apply our method to the benchmark proposed in prior work (Du et al., 2020), visualized in Fig. 3a. The four subplots show variant tasks of increasing complexity (more blocks), (± 1 SE). The prior approach (AvE (Du et al., 2020)) fails on all except the easiest task, highlighting the importance of scalability.

5.2 Does ESR scale to image-based observations?

Our second set of experiments look at scaling ESR to the image-based Overcooked environment. Since contrastive learning is often applied to image domains, we conjectured that ESR would scale gradefully to this setting. We will evaluate our approach in assisting a human policy trained with behavioral cloning taken from Laidlaw & Dragan (2022). The human prepares dishes by picking up ingredients and cooking them on a stove, while the AI assistant moves ingredients and dishes around the kitchen. We focus on two environments within this setting: a cramped room where the human must pass ingredients and dishes through a narrow corridor, and a coordination ring where the human must pass ingredients and dishes around a ring-shaped kitchen (Figs. 3b and 3c). As belore, we compare with AvE as well as a naïve random controller. We report results in Fig. 5. On both tasks, we observe that our approach achieves higher rewards than AvE baseline, which performs no better than a random controller. Taken together with the results in the previous setting, these results highlight the scalability of ESR to higher dimensional problems.

6 Discussion

One of the most important problems in AI today is equipping AI agents with the capacity to assist humans achieve their goals. While much of the amazing work in this area requires inferring the human's intention, our work builds on prior work in studying how an assistive agent can *empower* a human user without inferring their intention. Relative to prior methods, we demonstrate how empowerment can be readily estimated using contrastive learning, paving the way for deploying these techniques on high-dimensional problems.

Limitations. One of the main limitations of our approach is the assumption that the assistive agent has access to the human's actions, which could be challenging to observe in practice. Automatically inferring the human's actions remains an important problem for future work. A second limitation is that the method is currently an on-policy method, in the sense that the assistive agent has to learn by trial and error. Moving forward, we look forward to investigating techniques from off-policy evaluation and cooperative game theory to enable faster learning of assistive agents with fewer trials.

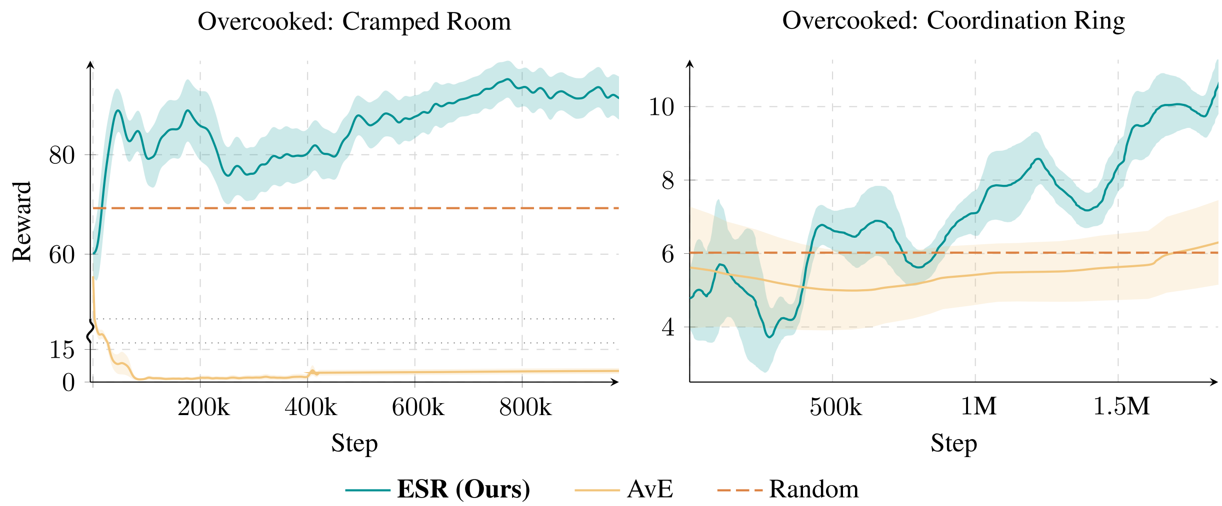


Figure 5: We test our approach in the Overcooked environment (Carroll et al., 2020). Our approach outperforms the prior method (AvE (Du et al., 2020)) and random selection without access to the human reward function (plotted ± 1SE.)

Safety risks. Perhaps the main risk involved with maximizing empowerment is that it may be at odds with a human's agents goal, especially in contexts where the pursuit of that goal limit's the human's capacity to persue other goals. For example, a family choosing to have a kid has many fewer options over where they can travel for vacation, yet we do not want assistive agents to stymie families from having children.

One key consideration is *whom* should be empowered. The present paper assumes there is a single human agent. Equivalently, this can be seen as maximizing the empowerment of all exogenous agents. However, it is easy to adapt the proposed method to maximize the empowerment of a single target individual. Given historical inequities in the distribution of power, practitioners must take care when considering who's empowerment to maximize. Similarly, while we focused on *maximizing* empowerment, it is trivial to change the sign so that an "assistive" agent minimizes empowerment. One could imagine using such a tool in policies to handicap one's political opponents.

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A Experimental Details

We ran all our experiments on NVIDIA RTX A6000 GPUs with 48GB of memory within an internal cluster. Each evaluation seed took around 5-10 hours to complete. Our losses (Eqs. (7) and (11)) were computed and optimized in JAX with Adam (Kingma & Ba, 2017). The experimental results described in Section 5 were obtained by averaging over 5 seeds for the Overcooked coordination ring layout, 15 for the cramped room layout, and 20 for the obstacle gridworld environment. Specific hyperparameter values can be found in our code, which is available at `https://anonymous.4open.science/r/esr-7E94`.

B The Information Geometry of Empowerment

This section considers an objective that might be slightly different: $I^{\pi_R}(\mathfrak{s}^+; z)$, where z is a representation of the human's intention. In practice, this could be represented as a sequence of actions (as in the main doc above), but it also includes reactive and closed loop policies. This mutual information also depends on the human's policy π_H, but here we are interested in just the dependence on the robot.

Here's the primary question of interest: what actions/behaviors should the robot employ to maximize the mutual information between the human's intentions and the outcomes. Note that this is a standard mutual information skill learning objective. However, whereas prior work typically optimizes this objective w.r.t. the human's policy $\pi_H(a \mid s, z)$, here we aim to optimize this w.r.t. the robot's policy $\pi_R(a \mid s)$. Note that the robot is not conditioned on the human's intention z. We assume that this intention is not observed. [1] The objective can then be written as

$$\max_{\pi_R} I^{\pi_R}(\mathfrak{s}^+; z). \tag{12}$$

One way of thinking about this optimization problem is that we are modifying the MDP itself. However, rather than (say) changing the positions of clouds or changing the framerate, we will only consider changes that can be mediated by an interactive robot agent. These include changes such as pushing an object, opening a drawer, charging or discharging another robot.

B.1 Preliminaries: Relating Mutual Information to Reward Maximization

The mutual information is an information theoretic quantity, defined in terms of bits and probabilities. However, what we actually care about is the ability of an assisted human to achieve high rewards. So, we need a way of relating this mutual information objective to reward maximizing. We start by recalling the result from Eysenbach et al. (2021), which provides one such relation:

$$\max_{\pi_H(z)} I(\mathfrak{s}^+; z) = \min_{\rho(s)\in\mathcal{C}} \max_{r(s)} \min_{\rho^*\in\mathcal{C}} \underbrace{\max_{\rho^+\in\mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)]}_{\text{regret}} + D_{\mathrm{KL}}(\rho^*(s)\|\rho(s)). \tag{13}$$

Unpacking this objective. There's a lot of math in that equation, so let's unpack it a bit. The LHS is about learning skills for the human policy π_H. We assume that all possible skills are enumerated, so the human simply has to select from this menu of skills by deciding much more of each skill $\pi_H(z)$ to order from this menu. Of course, this menu is exponentially long, but it is finite and well defined, and practical algorithms won't actually attempt to enumerate this menu of skills. The optimization problem on the LHS is about selecting those skills that most readily maximize the mutual information – the skills that have a strong influence over the states visited in the future.

The RHS has a whole bunch of terms. For a given reward function $r(s)$, we care about how much reward a particular policy gets. The RHS studies this standard expected reward by using the dual of the RL problem, thinking about the states $\rho(s)$ visited by a policy and counting up the rewards at those states. The term $\mathbb{E}_{\rho^+(s)}[r(s)]$ is the expected reward for a policy with occupancy measure $\rho^+(s)$. Thus, $\max_{\rho^+(s)} \mathbb{E}_{\rho^+(s)}[r(s)]$ is the maximal reward that any policy can get on this particular reward function.

We are often given a policy (or its occupancy measure $\rho^*(s)$) and and reward function $r(s)$ and want to know how good that policy is for that reward function. While we could directly measure the expected reward, we usually don't know whether

[1] One area for future work is to study whether actively inferring this intention improves assistance. Another area for future work is to study whether non-Markovian robot policies can perform better than their Markovian counterparts because they can accumulate information about the human's intentions across time.

this is a particularly good value or not. Instead, we might measure the *regret* of the policy: how much *lower* is its expected reward, as compared to the optimal policy for that reward function:

$$\textsc{Regret}(\rho(s)^*, r(s)) = \max_{\rho^+(s)} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)]. \tag{14}$$

This is the term that appears on the RHS on Eq. 13. Now, when we have limited data, we usually want to minimize a regularized notion of regret. This is what ρ^* is doing, using the KL divergence against a prior $\rho(s)$ as the regularization term:

$$\min_{\rho^*(s)} \textsc{Regret}(\rho^*(s), r(s)) + D_{\text{KL}}(\rho^*(s) \| \rho(s)). \tag{15}$$

This objective above can be interpreted as the difficulty of learning to maximize reward function $r(s)$. But, in the unsupervised RL setting, which reward functions should we learn how to optimize? We could take an average case approach, but this runs into challenges because "average" depends on a choice of measure. Instead, we take a worst-case approach, selecting the reward function that is most challenging to adapt to:

$$\max_{r(s)} \min_{\rho^*(s)} \textsc{Regret}(\rho^*(s), r(s)) + D_{\text{KL}}(\rho^*(s) \| \rho(s)). \tag{16}$$

Finally, when discussing adaptation, we had some prior $\rho(s)$ to which we were referring. The overall aim is to find the prior $\rho(s)$ that makes it easy to adapt to the most challenging reward function:

$$\min_{\rho(s) \in \mathcal{C}} \max_{r(s)} \textsc{AdaptationObjective}(\rho(s), r(s)). \tag{17}$$

Eq. 13 tells us that the problem of finding this optimal prior is equivalent to maximizing mutual information.

B.2 Application to Empowerment

We can extend this result to the assistive setting, thinking about how an assistive robot should act to make it easier for a human to maximize their worst-case rewards. From the human's perspective, the robot is just another part of the MDP.[2] So, to apply the result from Eq. 13 to empowerment, we just need to modify the definitions to depend on the choice of π_R.

On the LHS, let's use $I^{\pi_R}(\mathfrak{s}^+; z)$ to denote the mutual information between the *human's* choice of skills $\pi_H(z)$ and the future states, when interacting in an environment alongside a robot $\pi_R(a \mid s)$. The RHS thinks about the state occupancy measure of the human, terms like $\rho(s), \rho^+(s), \rho^*(s)$. An effective assistive agent will enable a human to visit a wide distribution over states, or to spend more time visiting any given state. We will use $\mathcal{C}^{\pi_R}$ to denote the feasible occupancy measures when interacting alongside an assistive agent.

B.3 Assistive Agents Minimize Regret

We can now state our main result, which is a direct corollary of Eq. 13 Consider the human and the robot as one monolithic agent selecting actions $a_H, a_R \sim \pi_H(a_H \mid s, z)\pi_R(a_R \mid s)$. This policy is Markovian, so we can immediately apply Eq. 13.

We start with some intuition: we would like an assistive agent to help the human maximize rewards. The challenge is that the assistive agent doesn't know what reward function the human is trying to solve, and we would like to avoid this inverse RL problem. So, we will take a worst-case approach, thinking about how the assistive agent can help the human solve the hardest task. We will measure difficulty as a combination of (1) regret versus the optimal policy, and (2) divergence from a prior over policies.

Notation. Let $\mathcal{C}^{\pi_R}$ denote the set of feasible state marginal distributions with cooperating with assistive agent $\pi_R(a \mid s)$. We assume that this assistive agent does not know the human's intention. We will measure regret against an omniscient assistive agent, which knows the human's intent. Thus, we compare to an occupancy measure optimized within the larger set $\mathcal{C}$, which includes adaptive strategies.

Assume human $\pi_H(a \mid s)$ and robot $\pi_R(a \mid s)$ induce state occupancy measure $\rho^*(s)$. We define their regret, which is measured relative to the highest reward they could achieve with *any* assistive agent (hence, we use $\rho^+ \in \mathcal{C}$ rather than $\rho^+ \in \mathcal{C}^{\pi_R}$):

$$\max_{\rho^+ \in \mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)].$$

[2]The reason we wanted to assume that the robot was Markovian was so that this remains a *Markov* decision process.

We will include an additional regularization term, so the overall objective becomes

$$\max_{\rho^+\in\mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)] + D_{\mathrm{KL}}(\rho^*(s)\|\rho(s)).$$

Given a reward function $r(s)$, we assume that the human adapts by minimizing this regularized regret. We assume that the assistive agent does not adapt. Thus, the human is optimizing over the smaller set $\mathcal{C}^{\pi_R}$:

$$\min_{\rho^*\in\mathcal{C}^{\pi_R}} \max_{\rho^+\in\mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)] + D_{\mathrm{KL}}(\rho^*(s)\|\rho(s)).$$

As before, the reward function is adversarially chosen. And, the human's job is to find the prior $\rho(s)$ that is minimax optimal:

$$\min_{\rho(s)\in\mathcal{C}^{\pi_R}} \max_{r(s)} \min_{\rho^*\in\mathcal{C}^{\pi_R}} \max_{\rho^+\in\mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)] + D_{\mathrm{KL}}(\rho^*(s)\|\rho(s)).$$

Lemma 3. *Assume that a human has learned skills $\pi(a \mid s, z)$ by maximizing mutual information $I(\mathfrak{s}^+; z)$ and adapts to a reward function by minimizing the regularized regret:*

$$\min_{\rho^*\in\mathcal{C}^{\pi_R}} \max_{\rho^+\in\mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)] + D_{KL}(\rho^*(s)\|\rho(s)).$$

We assume that the human chooses the prior $\rho(s)$ that minimizes this regret for the worst-case choice of reward function (i.e., the minimax optimal prior). An assistive agent that maximizes $I^{\pi_R}(\mathfrak{s}^+; z)$ minimizes the worst-case (regularized) regret incurred by the human.

Letting $\pi_R^* \in \arg\max_{\pi_R} I^{\pi_R}(\mathfrak{s}^+; z)$, we have

$$\pi_R^* \in \arg\min_{\pi_R} \left(\min_{\rho(s)\in\mathcal{C}^{\pi_R}} \max_{r(s)} \min_{\rho^*\in\mathcal{C}^{\pi_R}} \max_{\rho^+\in\mathcal{C}} \mathbb{E}_{\rho^+(s)}[r(s)] - \mathbb{E}_{\rho^*(s)}[r(s)] + D_{KL}\big(\rho^*(s)\|\rho(s)\big) \right). \tag{18}$$

C Simplifying the Objective

The reward function in Eq. 11 is itself a random variable because it depends on future states g. This subsection describes how this randomness can be removed. To do this, we follow prior work (Wang & Isola, 2020; Eysenbach et al., 2024) in arguing that the learned representations $\psi(g)$ follow a Gaussian distribution:

Assumption 1 (Based on Wang & Isola (2020))**.** *The representations of future states $\psi(g)$ learned by contrastive learning have a marginal distribution that is Gaussian:*

$$p(\psi) = \int p(g)\delta(\psi = \psi(g))\,\mathrm{d}g \overset{d}{=} \mathcal{N}(0, I). \tag{19}$$

With this assumption, we can remove the random sampling of g from the reward function. We start by noting that the learned representations tell us the *relative* likelihood of seeing a future state (Eq. 10). Assumption 1 will allow us to convert these relative likelihoods into likelihoods.

$$\begin{aligned}
\mathbb{E}_{p(\mathfrak{s}^+|s,a^{\mathbf{R}},a^{\mathbf{H}})}[r(s,a^{\mathbf{R}})] &= \mathbb{E}_{p(\mathfrak{s}^+)}\left[\tfrac{p(\mathfrak{s}^+|s,a^{\mathbf{R}},a^{\mathbf{H}})}{p(\mathfrak{s}^+)} r(s,a^{\mathbf{R}})\right] \\
&= \mathbb{E}_{p(\mathfrak{s}^+)}\left[C_1 e^{\phi(s,a^{\mathbf{R}},a^{\mathbf{H}})^T \phi(\mathfrak{s}^+)} r(s,a^{\mathbf{R}})\right] \\
&= C_1 \mathbb{E}_{\psi\sim p(\phi(\mathfrak{s}^+))}\left[e^{\phi(s,a^{\mathbf{R}},a^{\mathbf{H}})^T\psi} (\phi(s,a^{\mathbf{R}},a^{\mathbf{H}}) - \phi(s,a^{\mathbf{R}}))^T\psi\right] \\
&= C_1 \big(\phi(s,a^{\mathbf{R}},a^{\mathbf{H}}) - \phi(s,a^{\mathbf{R}})\big)^T \int \tfrac{1}{(2\pi)^{d/2}} e^{-\frac{1}{2}\|\psi\|_2^2 + \phi(s,a^{\mathbf{R}},a^{\mathbf{H}})^T\psi} \psi \,\mathrm{d}\psi \\
&= C_1 \big(\phi(s,a^{\mathbf{R}},a^{\mathbf{H}}) - \phi(s,a^{\mathbf{R}})\big)^T e^{\frac{1}{2}\|\phi(s,a^{\mathbf{R}},a^{\mathbf{H}})\|_2^2} \\
&\qquad \int \tfrac{1}{(2\pi)^{d/2}} e^{-\frac{1}{2}\|\psi\|_2^2 + \phi(s,a^{\mathbf{R}},a^{\mathbf{H}})^T\psi - \frac{1}{2}\|\phi(s,a^{\mathbf{R}},a^{H})\|_2^2} \psi\,\mathrm{d}\psi \\
&= C_1 \big(\phi(s,a^{\mathbf{R}},a^{\mathbf{H}}) - \phi(s,a^{\mathbf{R}})\big)^T e^{\frac{1}{2}\|\phi(s,a^{\mathbf{R}},a^{\mathbf{H}})\|_2^2} \mathbb{E}_{\psi\sim\mathcal{N}(\mu=\phi(s,a^{\mathbf{R}},a^{\mathbf{H}}),\Sigma=I)}\left[\psi\right] \\
&= C_1 e^{\frac{1}{2}\|\phi(s,a^{\mathbf{R}},a^{\mathbf{H}})\|_2^2} \big(\phi(s,a^{\mathbf{R}},a^{\mathbf{H}}) - \phi(s,a^{\mathbf{R}})\big)^T \phi(s,a^{\mathbf{R}},a^{\mathbf{H}}).
\end{aligned} \tag{20}$$