DARLA: Improving Zero-Shot Transfer in Reinforcement Learning

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Abstract

Domain adaptation is an important open problem in deep reinforcement learning (RL). In many scenarios of interest data is hard to obtain, so agents may learn a *source* policy in a setting where data is readily available, with the hope that it generalises well to the *target* domain. We propose a new multi-stage RL agent, DARLA (DisentAngled Representation Learning Agent), which learns to see before learning to act. DARLA's vision is based on learning a disentangled representation of the observed environment. Once DARLA can see, it is able to acquire source policies that are robust to many domain shifts - even with no access to the target domain. DARLA significantly outperforms conventional baselines in zero-shot domain adaptation scenarios, an effect that holds across a variety of RL environments (Jaco arm, DeepMind Lab) and base RL algorithms (DQN, A3C and EC).

1. Introduction

Autonomous agents can learn how to maximise future expected rewards by choosing how to act based on incoming sensory observations via reinforcement learning (RL). Early RL approaches did not scale well to environments with large state spaces and high-dimensional raw observations (Sutton & Barto, 1998). A commonly used workaround was to embed the observations in a lower-dimensional space, typically via hand-crafted and/or privileged-information features. Recently, the advent of deep learning and its successful combination with RL has enabled end-to-end learning of such embeddings directly from raw inputs, sparking success in a wide variety of previously challenging RL domains (Mnih et al., 2015; 2016; Jaderberg et al., 2017). Despite the seemingly universal efficacy of deep RL, however, fundamental issues remain. These include data inefficiency, the reactive nature and general brittleness of learnt policies to changes in input data distribution, and lack of model interpretability (Garnelo et al., 2016; Lake et al., 2016). This paper focuses on one of these outstanding issues: the ability of RL agents to deal with changes to the input distribution, a form of transfer learning known as *domain adaptation* (Bengio et al., 2013). In domain adaptation scenarios, an agent trained on a particular input distribution with a specified reward structure (termed the *source domain*) is placed in a setting where the input distribution is modified but the reward structure remains largely intact (the *target domain*). We aim to develop an agent that can learn a robust policy using observations and rewards obtained exclusively within the source domain. Here, a policy is considered as robust if it generalises with minimal drop in performance to the target domain without extra fine-tuning.

Past attempts to build RL agents with strong domain adaptation performance highlighted the importance of learning good internal representations of raw observations (Finn et al., 2015; Raffin et al., 2017; Pan & Yang, 2009; Barreto et al., 2016; Littman et al., 2001). Typically, these approaches tried to align the source and target domain representations by utilising observation and reward signals from both domains (Tzeng et al., 2016; Daftry et al., 2016; Parisotto et al., 2015; Guez et al., 2012; Talvitie & Singh, 2007; Niekum et al., 2013; Gupta et al., 2017; Finn et al., 2017; Rajendran et al., 2017). In many scenarios, such as robotics, this reliance on target domain information can be problematic, as the data may be expensive or difficult to obtain (Finn et al., 2017; Rusu et al., 2016). Furthermore, the target domain may simply not be known in advance. On the other hand, policies learnt exclusively on the source domain using existing deep RL approaches that have few constraints on the nature of the learnt representations often overfit to the source input distribution, resulting in poor domain adaptation performance (Lake et al., 2016; Rusu et al., 2016).

We propose tackling both of these issues by focusing instead on learning representations which capture an underlying low-dimensional factorised representation of the world and are therefore not task or domain specific. Many nat-

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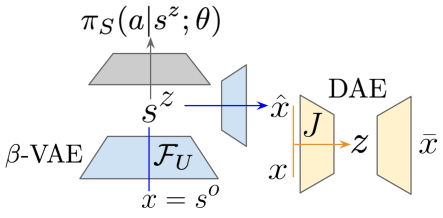

Figure 1. Schematic representation of DARLA. Yellow represents the denoising autoencoder part of the model, blue represents the β-VAE part of the model, and grey represents the policy learning part of the model.

uralistic domains such as video game environments, simulations and our own world are well described in terms of such a structure. Examples of such factors of variation are object properties like colour, scale, or position; other examples correspond to general environmental factors, such as geometry and lighting. We think of these factors as a set of high-level parameters that can be used by a world graphics engine to generate a particular natural visual scene (Kulkarni et al., 2015). Learning how to project raw observations into such a factorised description of the world is addressed by the large body of literature on disentangled representation learning (Schmidhuber, 1992; Desjardins et al., 2012; Cohen & Welling, 2014; 2015; Kulkarni et al., 2015; Hinton et al., 2011; Rippel & Adams, 2013; Reed et al., 2014; Yang et al., 2015; Goroshin et al., 2015; Kulkarni et al., 2015; Cheung et al., 2015; Whitney et al., 2016; Karaletsos et al., 2016; Chen et al., 2016; Higgins et al., 2017). Disentangled representations are defined as interpretable, factorised latent representations where either a single latent or a group of latent units are sensitive to changes in single ground truth factors of variation used to generate the visual world, while being invariant to changes in other factors (Bengio et al., 2013). The theoretical utility of disentangled representations for supervised and reinforcement learning has been described before (Bengio et al., 2013; Higgins et al., 2017; Ridgeway, 2016); however, to our knowledge, it has not been empirically validated to date.

We demonstrate how disentangled representations can improve the robustness of RL algorithms in domain adaptation scenarios by introducing *DARLA* (DisentAngled Representation Learning Agent), a new RL agent capable of learning a robust policy on the source domain that achieves significantly better out-of-the-box performance in domain adaptation scenarios compared to various baselines. DARLA relies on learning a latent state representation that is shared between the source and target domains, by learning a disentangled representation of the environment's generative factors. Crucially, DARLA does not require target domain data to form its representations. Our approach utilises a three stage pipeline: 1) learning to see, 2) learning to act, 3) transfer. During the first stage, DARLA develops its vision, learning to parse the world in terms of basic visual concepts, such as objects, positions, colours, etc. by utilising a stream of raw unlabelled observations – not unlike human babies in their first few months of life (Leat et al., 2009; Candy et al., 2009). In the second stage, the agent utilises this disentangled visual representation to learn a robust source policy. In stage three, we demonstrate that the DARLA source policy is more robust to domain shifts, leading to a significantly smaller drop in performance in the target domain even when no further policy finetuning is allowed (median 270.3% improvement). These effects hold consistently across a number of different RL environments (DeepMind Lab and Jaco/MuJoCo: Beattie et al., 2016; Todorov et al., 2012) and algorithms (DQN, A3C and Episodic Control: Mnih et al., 2015; 2016; Blundell et al., 2016).

2. Framework

2.1. Domain adaptation in Reinforcement Learning

We now formalise domain adaptation scenarios in a reinforcement learning (RL) setting. We denote the source and target domains as D_S and D_T, respectively. Each domain corresponds to an MDP defined as a tuple $D_S \equiv (\mathcal{S}_S, \mathcal{A}_S, \mathcal{T}_S, R_S)$ or $D_T \equiv (\mathcal{S}_T, \mathcal{A}_T, \mathcal{T}_T, R_T)$ (we assume a shared fixed discount factor γ), each with its own state space $\mathcal{S}$, action space $\mathcal{A}$, transition function $\mathcal{T}$ and reward function R.[1] In domain adaptation scenarios the states $\mathcal{S}$ of the source and the target domains can be quite different, while the action spaces $\mathcal{A}$ are shared and the transitions $\mathcal{T}$ and reward functions R have structural similarity. For example, consider a domain adaptation scenario for the Jaco robotic arm, where the MuJoCo (Todorov et al., 2012) simulation of the arm is the source domain, and the real world setting is the target domain. The state spaces (raw pixels) of the source and the target domains differ significantly due to the perceptual-reality gap (Rusu et al., 2016); that is to say, $\mathcal{S}_S \neq \mathcal{S}_T$. Both domains, however, share action spaces ($\mathcal{A}_S = \mathcal{A}_T$), since the policy learns to control the same set of actuators within the arm. Finally, the source and target domain transition and reward functions share structural similarity ($\mathcal{T}_S \approx \mathcal{T}_T$ and $R_S \approx R_T$), since in both domains transitions between states are governed by the physics of the world and the performance on the task depends on the relative position of the arm's end effectors (i.e. fingertips) with respect to an object of interest.

2.2. DARLA

In order to describe our proposed DARLA framework, we assume that there exists a set $\mathcal{M}$ of MDPs that is the set

[1]For further background on the notation relating to the RL paradigm, see Section A.1 in the Supplementary Materials.

of all *natural world* MDPs, and each MDP D_i is sampled from $\mathcal{M}$. We define $\mathcal{M}$ in terms of the state space $\hat{\mathcal{S}}$ that contains all possible conjunctions of high-level factors of variation necessary to generate any naturalistic observation in any $D_i \in \mathcal{M}$. A *natural world* MDP D_i is then one whose state space $\mathcal{S}$ corresponds to some subset of $\hat{\mathcal{S}}$. In simple terms, we assume that there exists *some* shared underlying structure between the MDPs D_i sampled from $\mathcal{M}$. We contend that this is a reasonable assumption that permits inclusion of many interesting problems, including being able to characterise our own reality (Lake et al., 2016).

We now introduce notation for two state space variables that may in principle be used interchangeably within the source and target domain MDPs D_S and D_T – the agent observation state space $\mathcal{S}^o$, and the agent's internal latent state space $\mathcal{S}^z$.[2] $\mathcal{S}_i^o$ in D_i consists of raw (pixel) observations s_i^o generated by the true world simulator from a sampled set of data generative factors $\hat{s}_i$, i.e. $s_i^o \sim \mathbf{Sim}(\hat{\mathbf{s}}_\mathbf{i})$. $\hat{s}_i$ is sampled by some distribution or process $\mathcal{G}_i$ on $\hat{\mathcal{S}}$, $\hat{s}_i \sim \mathcal{G}_i(\hat{\mathcal{S}})$.

Using the newly introduced notation, domain adaptation scenarios can be described as having different sampling processes $\mathcal{G}_S$ and $\mathcal{G}_T$ such that $\hat{s}_S \sim \mathcal{G}_S(\hat{\mathcal{S}})$ and $\hat{s}_T \sim \mathcal{G}_T(\hat{\mathcal{S}})$ for the source and target domains respectively, and then using these to generate different agent observation states $s_S^o \sim \mathbf{Sim}(\hat{\mathbf{s}}_\mathbf{S})$ and $s_T^o \sim \mathbf{Sim}(\hat{\mathbf{s}}_\mathbf{T})$. Intuitively, consider a source domain where oranges appear in blue rooms and apples appear in red rooms, and a target domain where the object/room conjunctions are reversed and oranges appear in red rooms and apples appear in blue rooms. While the true data generative factors of variation $\hat{\mathcal{S}}$ remain the same - room colour (blue or red) and object type (apples and oranges) - the particular source and target distributions $\mathcal{G}_S$ and $\mathcal{G}_T$ differ.

Typically deep RL agents (e.g. Mnih et al., 2015; 2016) operating in an MDP $D_i \in \mathcal{M}$ learn an end-to-end mapping from raw (pixel) observations $s_i^o \in \mathcal{S}_i^o$ to actions $a_i \in \mathcal{A}_i$ (either directly or via a value function $Q_i(s_i^o, a_i)$ from which actions can be derived). In the process of doing so, the agent implicitly learns a function $\mathcal{F} : \mathcal{S}_i^o \rightarrow \mathcal{S}_i^z$ that maps the typically high-dimensional raw observations s_i^o to typically low-dimensional latent states s_i^z; followed by a policy function $\pi_i : \mathcal{S}_i^z \rightarrow \mathcal{A}_i$ that maps the latent states s_i^z to actions $a_i \in \mathcal{A}_i$. In the context of domain adaptation, if the agent learns a naive latent state mapping function $\mathcal{F}_S : \mathcal{S}_S^o \rightarrow \mathcal{S}_S^z$ on the source domain using reward signals to shape the representation learning, it is likely that $\mathcal{F}_S$ will overfit to the source domain and will not generalise well to the target domain. Returning to our intuitive example, imagine an agent that has learnt a policy to pick up oranges and avoid apples on the source domain. Such a source policy π_S is likely to be based on an *entangled* latent state space $\mathcal{S}_S^z$ of object/room conjunctions: oranges/blue $\rightarrow$ good, apples/red $\rightarrow$ bad, since this is arguably the most efficient representation for maximising expected rewards on the source task in the absence of extra supervision signals suggesting otherwise. A source policy $\pi_S(a|s_S^z;\theta)$ based on such an entangled latent representation s_S^z will not generalise well to the target domain without further fine-tuning, since $\mathcal{F}_S(s_S^o) \neq \mathcal{F}_S(s_T^o)$ and therefore crucially $S_S^z \neq S_T^z$.

On the other hand, since both $\hat{s}_S \sim \mathcal{G}_S(\hat{\mathcal{S}})$ and $\hat{s}_T \sim \mathcal{G}_T(\hat{\mathcal{S}})$ are sampled from the same *natural world* state space $\hat{\mathcal{S}}$ for the source and target domains respectively, it should be possible to learn a latent state mapping function $\hat{\mathcal{F}} : \mathcal{S}^o \rightarrow \mathcal{S}_{\hat{\mathcal{S}}}^z$, which projects the agent observation state space $\mathcal{S}^o$ to a latent state space $\mathcal{S}_{\hat{\mathcal{S}}}^z$ expressed in terms of factorised data generative factors that are representative of the natural world i.e. $S_{\hat{\mathcal{S}}}^z \approx \hat{\mathcal{S}}$. Consider again our intuitive example, where $\hat{\mathcal{F}}$ maps agent observations (s_S^o: orange in a blue room) to a factorised or *disentangled* representation expressed in terms of the data generative factors ($s_{\hat{\mathcal{S}}}^z$: *room type* = blue; *object type* = orange). Such a *disentangled* latent state mapping function should then directly generalise to both the source and the target domains, so that $\hat{\mathcal{F}}(s_S^o) = \hat{\mathcal{F}}(s_T^o) = s_{\hat{\mathcal{S}}}^z$. Since $\mathcal{S}_{\hat{\mathcal{S}}}^z$ is a *disentangled* representation of object and room attributes, the source policy π_S can learn a decision boundary that ignores the irrelevant room attributes: oranges $\rightarrow$ good, apples $\rightarrow$ bad. Such a policy would then generalise well to the target domain out of the box, since $\pi_S(a|\hat{\mathcal{F}}(s_S^o);\theta) = \pi_T(a|\hat{\mathcal{F}}(s_T^o);\theta) = \pi_T(a|s_{\hat{\mathcal{S}}}^z;\theta)$. Hence, DARLA is based on the idea that a good quality $\hat{\mathcal{F}}$ learnt exclusively on the source domain $D_S \in \mathcal{M}$ will zero-shot-generalise to all target domains $D_i \in \mathcal{M}$, and therefore the source policy $\pi(a|\mathcal{S}_{\hat{\mathcal{S}}}^z;\theta)$ will also generalise to all target domains $D_i \in \mathcal{M}$ out of the box.

Next we describe each of the stages of the DARLA pipeline that allow it to learn source policies π_S that are robust to domain adaptation scenarios, despite being trained with no knowledge of the target domains (see Fig. 1 for a graphical representation of these steps):

1) Learn to see (unsupervised learning of $\mathcal{F}_U$) – the task of inferring a factorised set of generative factors $\mathcal{S}_{\hat{\mathcal{S}}}^z = \hat{\mathcal{S}}$ from observations $\mathcal{S}^o$ is the goal of the extensive disentangled factor learning literature (e.g. Chen et al., 2016; Higgins et al., 2017). Hence, in stage one we learn a mapping $\mathcal{F}_U : \mathcal{S}_U^o \rightarrow \mathcal{S}_U^z$, where $\mathcal{S}_U^z \approx \mathcal{S}_{\hat{\mathcal{S}}}^z$ (U stands for 'unsupervised') using an unsupervised model for learning disentangled factors that utilises observations collected by an agent with a random policy π_U from a visual pre-training

[2] Note that we do not assume these to be Markovian i.e. it is not necessarily the case that $p(s_{t+1}^o|s_t^o) = p(s_{t+1}^o|s_t^o, s_{t-1}^o, \ldots, s_1^o)$, and similarly for s^z. Note the index t here corresponds to time.

MDP $D_U \in \mathcal{M}$. Note that we require sufficient variability of factors and their conjunctions in D_U in order to have $S^z_U \approx \mathcal{S}^z_{\hat{S}}$;

2) Learn to act (reinforcement learning of π_S in the source domain D_S utilising previously learned $\mathcal{F}_U$) – an agent that has learnt to see the world in stage one in terms of the natural data generative factors is now exposed to a source domain $D_S \in \mathcal{M}$. The agent is tasked with learning the source policy $\pi_S(a|s^z_S;\theta)$, where $s^z_S = \mathcal{F}_U(s^o_S) \approx s^z_{\hat{S}}$, via a standard reinforcement learning algorithm. Crucially, we do not allow $\mathcal{F}_U$ to be modified (e.g. by gradient updates) during this phase;

3) Transfer (to a target domain D_T) – in the final step, we test how well the policy π_S learnt on the source domain generalises to the target domain $D_T \in \mathcal{M}$ in a zero-shot domain adaptation setting, i.e. the agent is evaluated on the target domain without retraining. We compare the performance of policies learnt with a disentangled latent state $\mathcal{S}^z_{\hat{S}}$ to various baselines where the latent state mapping function $\mathcal{F}_U$ projects agent observations s^o to entangled latent state representations s^z.

2.3. Learning disentangled representations

In order to learn $\mathcal{F}_U$, DARLA utilises β-VAE (Higgins et al., 2017), a state-of-the-art unsupervised model for automated discovery of factorised latent representations from raw image data. β-VAE is a modification of the variational autoencoder framework (Kingma & Welling, 2014; Rezende et al., 2014) that controls the nature of the learnt latent representations by introducing an adjustable hyperparameter β to balance reconstruction accuracy with latent channel capacity and independence constraints. It maximises the objective:

$$\mathcal{L}(\theta, \phi; \mathbf{x}, \mathbf{z}, \beta) = E_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})] - \beta\, D_{KL}(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})) \quad (1)$$

where ϕ, θ parametrise the distributions of the encoder and the decoder respectively. Well-chosen values of β - usually larger than one ($\beta > 1$) - typically result in more disentangled latent representations $\mathbf{z}$ by limiting the capacity of the latent information channel, and hence encouraging a more efficient factorised encoding through the increased pressure to match the isotropic unit Gaussian prior $p(\mathbf{z})$ (Higgins et al., 2017).

2.3.1. Perceptual Similarity Loss

The cost of increasing β is that crucial information about the scene may be discarded in the latent representation $\mathbf{z}$, particularly if that information takes up a small proportion of the observations $\mathbf{x}$ in pixel space. We encountered this issue in some of our tasks, as discussed in Section 3.1. The shortcomings of calculating the log-likelihood term $E_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})]$ on a per-pixel basis are known and have been addressed in the past by calculating the reconstruction cost in an abstract, high-level feature space given by *another* neural network model, such as a GAN (Goodfellow et al., 2014) or a pre-trained AlexNet (Krizhevsky et al., 2012; Larsen et al., 2016; Dosovitskiy & Brox, 2016; Warde-Farley & Bengio, 2017). In practice we found that pre-training a denoising autoencoder (Vincent et al., 2010) on data from the visual pre-training MDP $D_U \in \mathcal{M}$ worked best as the reconstruction targets for β-VAE to match (see Fig. 1 for model architecture and Sec. A.3.1 in Supplementary Materials for implementation details). The new β-VAE$_{DAE}$ model was trained according to Eq. 2:

$$\mathcal{L}(\theta, \phi; \mathbf{x}, \mathbf{z}, \beta) = E_{q_\phi(\mathbf{z}|\mathbf{x})} \|J(\hat{\mathbf{x}}) - J(\mathbf{x})\|_2^2 - \beta\, D_{KL}(q_\phi(\mathbf{z}|\mathbf{x})||p(\mathbf{z})) \quad (2)$$

where $\hat{\mathbf{x}} \sim p_\theta(\mathbf{x}|\mathbf{z})$ and $J : R^{W\times H\times C} \rightarrow R^N$ is the function that maps images from pixel space with dimensionality $W \times H \times C$ to a high-level feature space with dimensionality N given by a stack of pre-trained DAE layers up to a certain layer depth. Note that by replacing the pixel based reconstruction loss in Eq. 1 with high-level feature reconstruction loss in Eq. 2 we are no longer optimising the variational lower bound, and β-VAE$_{DAE}$ with $\beta = 1$ loses its equivalence to the Variational Autoencoder (VAE) framework as proposed by (Kingma & Welling, 2014; Rezende et al., 2014). In this setting, the only way to interpret β is as a mixing coefficient that balances the capacity of the latent channel $\mathbf{z}$ of β-VAE$_{DAE}$ against the pressure to match the high-level features within the pre-trained DAE.

2.4. Reinforcement Learning Algorithms

We used various RL algorithms (DQN, A3C and Episodic Control: Mnih et al., 2015; 2016; Blundell et al., 2016) to learn the source policy π^S during stage two of the pipeline using the latent states s^z acquired by β-VAE based models during stage one of the DARLA pipeline.

Deep Q Network (DQN) (Mnih et al., 2015) is a variant of the Q-learning algorithm (Watkins, 1989) that utilises deep learning. It uses a neural network to parametrise an approximation for the action-value function $Q(s, a; \theta)$ using parameters θ.

Asynchronous Advantage Actor-Critic (A3C) (Mnih et al., 2016) is an asynchronous implementation of the advantage actor-critic paradigm (Sutton & Barto, 1998; Degris & Sutton, 2012), where separate threads run in parallel and perform updates to shared parameters. The different threads each hold their own instance of the environment and have different exploration policies, thereby decorrelating parameter updates without the need for experience replay. Therefore, A3C is an online algorithm, whereas DQN learns its policy offline, resulting in different learning dynamics be-

tween the two algorithms.

Model-Free Episodic Control (EC) (Blundell et al., 2016) was proposed as a complementary learning system to the other RL algorithms described above. The EC algorithm relies on near-determinism of state transitions and rewards in RL environments; in settings where this holds, it can exploit these properties to memorise which action led to high returns in similar situations in the past. Since in its simplest form EC relies on a lookup table, it learns good policies much faster than value-function-approximation based deep RL algorithms like DQN trained via gradient descent - at the cost of generality (i.e. potentially poor performance in non-deterministic environments).

We also compared our approach to that of *UNREAL* (Jaderberg et al., 2017), a recently proposed RL algorithm which also attempts to utilise unsupervised data in the environment. The UNREAL agent takes as a base an LSTM A3C agent (Mnih et al., 2016) and augments it with a number of unsupervised auxiliary tasks that make use of the rich perceptual data available to the agent besides the (sometimes very sparse) extrinsic reward signals. This auxiliary learning tends to improve the representation learnt by the agent. See Sec. A.6 in Supplementary Materials for further details of the algorithms above.

3. Tasks

We evaluate the performance of DARLA on different task and environment setups that probe subtly different aspects of domain adaptation. As a reminder, in Sec. 2.2 we defined $\hat{\mathcal{S}}$ as a state space that contains all possible conjunctions of high-level factors of variation necessary to generate any naturalistic observation in any $D_i \in \mathcal{M}$. During domain adaptation scenarios agent observation states are generated according to $s_S^o \sim \mathbf{Sim_S}(\hat{\mathbf{s}}_\mathbf{S})$ and $s_T^o \sim \mathbf{Sim_T}(\hat{\mathbf{s}}_\mathbf{T})$ for the source and target domains respectively, where $\hat{s}_S$ and $\hat{s}_T$ are sampled by some distributions or processes $\mathcal{G}_S$ and $\mathcal{G}_T$ according to $\hat{s}_S \sim \mathcal{G}_S(\hat{\mathcal{S}})$ and $\hat{s}_T \sim \mathcal{G}_T(\hat{\mathcal{S}})$.

We use DeepMind Lab (Beattie et al., 2016) to test a version of domain adaptation setup where the source and target domain observation simulators are equal ($\mathbf{Sim_S} = \mathbf{Sim_T}$), but the processes used to sample $\hat{s}_S$ and $\hat{s}_T$ are different ($\mathcal{G}_S \neq \mathcal{G}_T$). We use the Jaco arm with a matching MuJoCo simulation environment (Todorov et al., 2012) in two domain adaptation scenarios: simulation to simulation (sim2sim) and simulation to reality (sim2real). The sim2sim domain adaptation setup is relatively similar to DeepMind Lab i.e. the source and target domains differ in terms of processes $\mathcal{G}_S$ and $\mathcal{G}_T$. However, there is a significant point of difference. In DeepMind Lab, all values of factors in the target domain, $\hat{s}_T$, are previously seen in the source domain; however, $\hat{s}_S \neq \hat{s}_T$ as the *conjunctions* of these factor values are different. In sim2sim, by contrast, novel factor *values* are experienced in the target domain (this accordingly also leads to novel factor conjunctions). Hence, DeepMind Lab may be considered to be assessing domain *interpolation* performance, whereas sim2sim tests domain *extrapolation*.

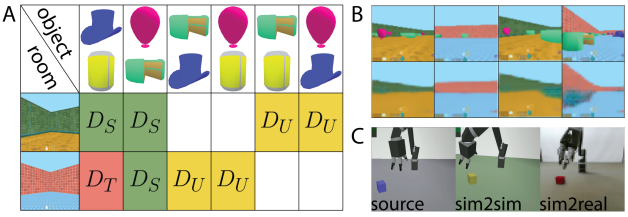

Figure 2. **A**: DeepMind Lab (Beattie et al., 2016) transfer task setup. Different conjunctions of {room, object$_1$, object$_2$} were used during different parts of the domain adaptation curriculum. During stage one, D_U (shown in yellow), we used a minimal set spanning all objects and all rooms whereby each object is seen in each room. Note there is no extrinsic reward signal or notion of 'task' in this phase. During stage two, D_S (shown in green), the RL agents were taught to pick up cans and balloons and avoid hats and cakes. The objects were always presented in pairs hat/can and cake/balloon. The agent never saw the hat/can pair in the pink room. This novel room/object conjunction was presented as the target domain adaptation condition D_T (shown in red) where the ability of the agent to transfer knowledge of the objects' value to a novel environment was tested. **B**: β-VAE reconstructions (bottom row) using frames from DeepMind Lab (top row). Due to the increased $\beta > 1$ necessary to disentangle the data generative factors of variations the model lost information about objects. See Fig. 3 for a model appropriately capturing objects. **C**: *left* – sample frames from MuJoCo simulation environments used for vision (phase 1, S_U) and source policy training (phase 2, S_S); *middle* – sim2sim domain adaptation test (phase 3, S_T); and *right* – sim2real domain adaptation test (phase 3, S_T).

The sim2real setup, on the other hand, is based on identical processes $\mathcal{G}_S = \mathcal{G}_T$, but different observation simulators $\mathbf{Sim_S} \neq \mathbf{Sim_T}$ corresponding to the MuJoCo simulation and the real world, which results in the so-called 'perceptual reality gap' (Rusu et al., 2016). More details of the tasks are given below.

3.1. DeepMind Lab

DeepMind Lab is a first person 3D game environment with rich visuals and realistic physics. We used a standard seek-avoid object gathering setup, where a room is initialised with an equal number of randomly placed objects of two different types. One of the object varieties is 'good' (its collection is rewarded +1), while the other is 'bad' (its collection is punished -1). The full state space $\hat{\mathcal{S}}$ consisted of all conjunctions of two room types (pink and green based on the colour of the walls) and four object types (hat, can, cake and balloon) (see Fig. 2A). The source domain D_S con-

tained environments with hats/cans presented in the green room, and balloons/cakes presented in either the green or the pink room. The target domain D_T contained hats/cans presented in the pink room. In both domains cans and balloons were the rewarded objects.

1) Learn to see: we used β-VAE$_{DAE}$ to learn the disentangled latent state representation s^z that includes both the room and the object generative factors of variation within DeepMind Lab. We had to use the high-level feature space of a pre-trained DAE within the β-VAE$_{DAE}$ framework (see Section 2.3.1), instead of the pixel space of vanilla β-VAE , because we found that objects failed to reconstruct when using the values of β necessary to disentangle the generative factors of variation within DeepMind Lab (see Fig. 2B).

β-VAE$_{DAE}$ was trained on observations s^o_U collected by an RL agent with a simple wall-avoiding policy π_U (otherwise the training data was dominated by close up images of walls). In order to enable the model to learn $\mathcal{F}(s^o_U) \approx \hat{\mathcal{S}}$, it is important to expose the agent to at least a minimal set of environments that span the range of values for each factor, and where no extraneous correlations are added between different factors[3](see Fig. 2A, yellow). See Section A.3.1 in Supplementary Materials for details of β-VAE$_{DAE}$ training.

2) Learn to act: the agent was trained with the algorithms detailed in Section 2.4 on a seek-avoid task using the source domain (D_S) conjunctions of object/room shown in Fig. 2A (green). Pre-trained β-VAE$_{DAE}$ from stage one was used as the 'vision' part of various RL algorithms (DQN, A3C and Episodic Control: Mnih et al., 2015; 2016; Blundell et al., 2016) to learn a source policy π_S that picks up balloons and avoids cakes in both the green and the pink rooms, and picks up cans and avoids hats in the green rooms. See Section A.3.1 in Supplementary Materials for more details of the various versions of DARLA we have tried, each based on a different base RL algorithm.

3) Transfer: we tested the ability of DARLA to transfer the seek-avoid policy π_S it had learnt on the source domain in stage two using the domain adaptation condition D_T illustrated in Figure 2A (red). The agent had to continue picking up cans and avoid hats in the pink room, even though these objects had only been seen in the green room during source policy training. The optimal policy π_T is one that maintains the reward polarity from the source domain (cans are good and hats are bad). For further details, see Appendix A.2.1.

[3]In our setup of DeepMind Lab domain adaptation task, the object and environment factors are supposed to be independent. In order to ensure that β-VAE$_{DAE}$ learns a factorised representation that reflects this ground truth independence, we present observations of all possible conjunctions of room and individual object types.

3.2. Jaco Arm and MuJoCo

We used frames from an RGB camera facing a robotic Jaco arm, or a matching rendered camera view from a MuJoCo physics simulation environment (Todorov et al., 2012) to investigate the performance of DARLA in two domain adaptation scenarios: 1) simulation to simulation (sim2sim), and 2) simulation to reality (sim2real). The sim2real setup is of particular importance, since the progress that deep RL has brought to control tasks in simulation (Schulman et al., 2015; Mnih et al., 2016; Levine & Abbeel, 2014; Heess et al., 2015; Lillicrap et al., 2015; Schulman et al., 2016) has not yet translated as well to reality, despite various attempts (Tobin et al., 2017; Tzeng et al., 2016; Daftry et al., 2016; Finn et al., 2015; Rusu et al., 2016). Solving control problems in reality is hard due to sparse reward signals, expensive data acquisition and the attendant danger of breaking the robot (or its human minders) during exploration.

In both sim2sim and sim2real, we trained the agent to perform an object reaching policy where the goal is to place the end effector as close to the object as possible. While conceptually the reaching task is simple, it is a hard control problem since it requires correct inference of the arm and object positions and velocities from raw visual inputs.

1) Learn to see: β-VAE was trained on observations collected in MuJoCo simulations with the same factors of variation as in D_S. In order to enable the model to learn $\mathcal{F}(s^o_U) \approx \hat{s}$, a reaching policy was applied to phantom objects placed in random positions - therefore ensuring that the agent learnt the independent nature of the arm position and object position (see Fig. 2C, left);

2) Learn to act: a feedforward-A3C based agent with the vision module pre-trained in stage one was taught a source reaching policy π_S towards the real object in simulation (see Fig. 2C (left) for an example frame, and Sec. A.4 in Supplementary Materials for a fuller description of the agent). In the source domain D_S the agent was trained on a distribution of camera angles and positions. The colour of the tabletop on which the arm rests and the object colour were both sampled anew every episode.

3) Transfer: **sim2sim**: in the target domain, D_T, the agent was faced with a new distribution of camera angles and positions with little overlap with the source domain distributions, as well as a completely held out set of object colours (see Fig. 2C, middle). **sim2real**: in the target domain D_T the camera position and angle as well as the tabletop colour and object colour were sampled from the same distributions as seen in the source domain D_S, but the target domain D_T was now the real world. Many details present in the real world such as shadows, specularity, multiple light sources and so on are not modelled in the simulation;

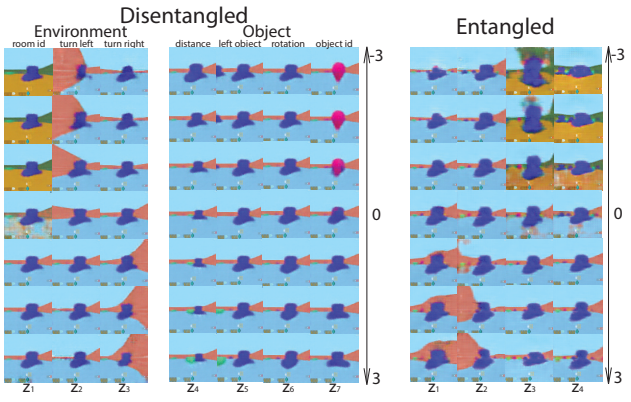

Figure 3. Plot of traversals of various latents of an entangled and a disentangled version of β-VAE$_{DAE}$ using frames from DeepMind Lab (Beattie et al., 2016).

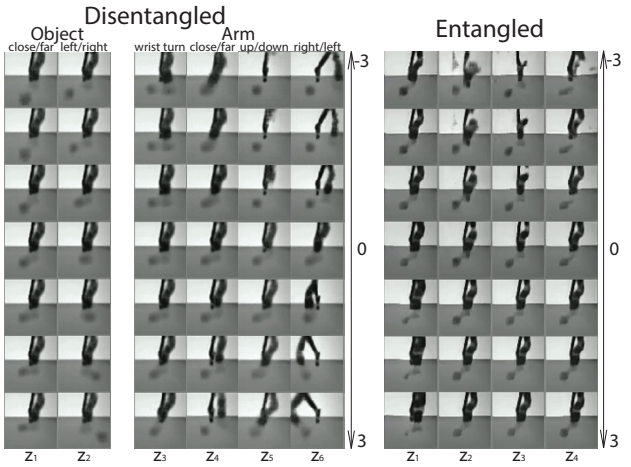

Figure 4. Plot of traversals of β-VAE on MuJoCo. Using a disentangled β-VAE model, single latents directly control for the factors responsible for the object or arm placements.

the physics engine is also not a perfect model of reality. Thus sim2real tests the ability of the agent to cross the perceptual-reality gap and generalise its source policy π_S to the real world (see Fig. 2C, right). For further details, see Appendix A.2.2.

4. Results

We evaluated the robustness of DARLA's policy π_S learnt on the source domain to various shifts in the input data distribution. In particular, we used domain adaptation scenarios based on the DeepMind Lab seek-avoid task and the Jaco arm reaching task described in Sec. 3. On each task we compared DARLA's performance to that of various baselines. We evaluated the importance of learning 'good' vision during stage one of the pipeline, i.e one that maps the input observations s^o to disentangled representations $s^z \approx \hat{s}$. In order to do this, we ran the DARLA pipeline with different vision models: the encoders of a disentangled β-VAE [4] (the original DARLA), an *entangled* β-VAE (DARLA$_{\text{ENT}}$), and a denoising autoencoder (DARLA$_{\text{DAE}}$). Apart from the nature of the learnt representations s^z, DARLA and all versions of its baselines were equivalent throughout the three stages of our proposed pipeline in terms of architecture and the observed data distribution (see Sec. A.3 in Supplementary Materials for more details).

Figs. 3-4 display the degree of disentanglement learnt by the vision modules of DARLA and DARLA$_{\text{ENT}}$ on DeepMind Lab and MuJoCo. DARLA's vision learnt to independently represent environment variables (such as room colour-scheme and geometry) and object-related variables (change of object type, size, rotation) on DeepMind Lab (Fig. 3, left). Disentangling was also evident in MuJoCo. Fig. 4, left, shows that DARLA's single latent units z_i learnt to represent different aspects of the Jaco arm, the object, and the camera. By contrast, in the representations learnt by DARLA$_{\text{ENT}}$, each latent is responsible for changes to both the environment and objects (Fig. 3, right) in DeepMind Lab, or a mixture of camera, object and/or arm movements (Fig. 4, right) in MuJoCo.

The table in Fig. 5 shows the average performance (across different seeds) in terms of rewards per episode of the various agents on the target domain with no fine-tuning of the source policy π_S. It can be seen that DARLA is able to zero-shot-generalise significantly better than DARLA$_{\text{ENT}}$ or DARLA$_{\text{DAE}}$, highlighting the importance of learning a disentangled representation $s^z = s^z_{\hat{S}}$ during the unsupervised stage one of the DARLA pipeline. In particular, this also demonstrates that the improved domain transfer performance is not simply a function of increased exposure to training observations, as both DARLA$_{\text{ENT}}$ and DARLA$_{\text{DAE}}$ were exposed to the same data. The results are mostly consistent across target domains and in most cases DARLA is significantly better than the second-best-performing agent. This holds in the sim2real task [5], where being able to perform zero-shot policy transfer is highly valuable due to the particular difficulties of gathering data in the real world.

DARLA's performance is particularly surprising as it actually preserves *less* information about the raw observations s^o than DARLA$_{\text{ENT}}$ and DARLA$_{\text{DAE}}$. This is due to the nature of the β-VAE and how it achieves disentangling; the disentangled model utilised a significantly higher value of the hyperparameter β than the entangled model (see Appendix A.3 for further details), which constrains the ca-

[4] In this section of the paper, we use the term β-VAE to refer to a standard β-VAE for the MuJoCo experiments, and a β-VAE$_{DAE}$ for the DeepMind Lab experiments (as described in stage 1 of Sec. 3.1).

[5] See https://youtu.be/sZqrWFl0wQ4 for example sim2sim and sim2real zero-shot transfer policies of DARLA and baseline A3C agent.

Table 1. Transfer performance

Vision Type	DeepMind Lab DQN	DeepMind Lab A3C	DeepMind Lab EC	Jaco (A3C) sim2sim	Jaco (A3C) sim2real
Baseline agent	1.86 ± 3.91	5.32 ± 3.36	-0.41 ± 4.21	97.64 ± 9.02	94.56 ± 3.55
UNREAL	-	4.13 ± 3.95	-	-	-
DARLA_{FT}	$\mathbf{13.36 \pm 5.8}$	1.4 ± 2.16	-	86.59 ± 5.53	99.25 ± 2.3
$\text{DARLA}_{\text{ENT}}$	3.45 ± 4.47	15.66 ± 5.19	5.69 ± 3.73	84.77 ± 4.42	59.99 ± 15.05
$\text{DARLA}_{\text{DAE}}$	7.83 ± 4.47	6.74 ± 2.81	5.59 ± 3.37	85.15 ± 7.43	100.72 ± 4.7
DARLA	10.25 ± 5.46	$\mathbf{19.7 \pm 5.43}$	$\mathbf{11.41 \pm 3.52}$	$\mathbf{100.85 \pm 2.92}$	$\mathbf{108.2 \pm 5.97}$

DARLA's performance is significantly different from all baselines under Welch's unequal variances t-test with $p < 0.01$ ($N \in [60, 150]$).

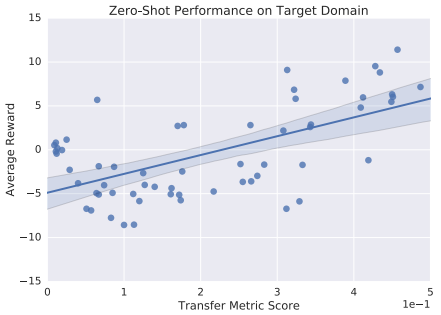

Figure 5. **Table**: Zero-shot performance (avg. reward per episode) of the source policy π_S in target domains within DeepMind Lab and Jaco/MuJoCo environments. Baseline agent refers to vanilla DQN/A3C/EC (DeepMind Lab) or A3C (Jaco) agents. See main text for more detailed model descriptions. **Figure**: Correlation between zero-shot performance transfer performance on the DeepMind Lab task obtained by EC based DARLA and the level of disentanglement as measured by the transfer/disentanglement score ($r = 0.6, p < 0.001$)

pacity of the latent channel. Indeed, DARLA's β-VAE only utilises 8 of its possible 32 Gaussian latents to store observation-specific information for MuJoCo/Jaco (and 20 in DeepMind Lab), whereas $\text{DARLA}_{\text{ENT}}$ utilises all 32 for both environments (as does $\text{DARLA}_{\text{DAE}}$).

Furthermore, we examined what happens if DARLA's vision (i.e. the encoder of the disentangled β-VAE) is allowed to be fine-tuned via gradient updates while learning the source policy during stage two of the pipeline. This is denoted by DARLA_{FT} in the table in Fig. 5. We see that it exhibits significantly worse performance than that of DARLA in zero-shot domain adaptation using an A3C-based agent in all tasks. This suggests that a favourable initialisation does not make up for subsequent overfitting to the source domain for the on-policy A3C. However, the off-policy DQN-based fine-tuned agent performs very well. We leave further investigation of this curious effect for future work.

Finally, we compared the performance of DARLA to an UNREAL (Jaderberg et al., 2017) agent with the same architecture. Despite also exploiting the unsupervised data available in the source domain, UNREAL performed worse than baseline A3C on the DeepMind Lab domain adaptation task. This further demonstrates that use of unsupervised data in itself is not a panacea for transfer performance; it must be utilised in a careful and structured manner conducive to learning disentangled latent states $s^z = s^z_{\hat{S}}$.

In order to quantitatively evaluate our hypothesis that disentangled representations are essential for DARLA's performance in domain adaptation scenarios, we trained various DARLAs with different degrees of learnt disentanglement in s^z by varying β (of β-VAE) during stage one of the pipeline. We then calculated the correlation between the performance of the EC-based DARLA on the DeepMind Lab domain adaptation task and the transfer metric, which approximately measures the quality of disentanglement of DARLA's latent representations s^z (see Sec. A.5.2 in Supplementary Materials). This is shown in the chart in Fig. 5; as can be seen, there is a strong positive correlation between the level of disentanglement and DARLA's zero-shot domain transfer performance ($r = 0.6, p < 0.001$).

Having shown the robust utility of disentangled representations in agents for domain adaptation, we note that there is evidence that they can provide an important additional benefit. We found significantly improved speed of learning of π_S on the source domain itself, as a function of how disentangled the model was. The gain in data efficiency from disentangled representations for source policy learning is not the main focus of this paper so we leave it out of the main text; however, we provide results and discussion in Section A.7 in Supplementary Materials.

5. Conclusion

We have demonstrated the benefits of using disentangled representations in a deep RL setting for domain adaptation. In particular, we have proposed DARLA, a multi-stage RL agent. DARLA first learns a visual system that encodes the observations it receives from the environment as disentangled representations, in a completely unsupervised manner. It then uses these representations to learn a robust source policy that is capable of zero-shot domain adaptation.

We have demonstrated the efficacy of this approach in a range of domains and task setups: a 3D naturalistic first-person environment (DeepMind Lab), a simulated graphics and physics engine (MuJoCo), and crossing the simulation to reality gap (MuJoCo to Jaco sim2real). We have also shown that the effect of disentangling is consistent across very different RL algorithms (DQN, A3C, EC), achieving significant improvements over the baseline algorithms (median 2.7 times improvement in zero-shot transfer across tasks and algorithms). To the best of our knowledge, this is the first comprehensive empirical demonstration of the strength of disentangled representations for domain adaptation in a deep RL setting.

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