**BRAXLINES: Fast and Interactive Toolkit for RL-driven Behavior Engineering beyond Reward Maximization**

Shixiang Shane Gu  
shaneGu@google.com

Manfred Diaz  
diazcabm@mila.quebec

Daniel C. Freeman  
cdfreeman@google.com

Hiroki Furuta  
furuta@weblab.t.u-tokyo.ac.jp

Seyed Kamyar Seyed Ghasemipour  
kamyar@cs.toronto.edu

Anton Raichuk  
raveman@google.com

Byron David  
byrondavid@google.com

Erik Frey  
erikfrey@google.com

Erwin Coumans  
erwincoumans@gmail.com

Olivier Bachem  
bachem@google.com

**Abstract**

The goal of continuous control is to synthesize desired behaviors. In reinforcement learning (RL)-driven approaches, this is often accomplished through careful task reward engineering for efficient exploration and running an off-the-shelf RL algorithm. While reward maximization is at the core of RL, reward engineering is not the only – sometimes nor the easiest – way for specifying complex behaviors. In this paper, we introduce BRAXLINES, a toolkit for fast and interactive RL-driven behavior generation beyond simple reward maximization that includes COMPOSER, a programmatic API for generating continuous control environments, and set of stable and well-tested baselines for two families of algorithms – mutual information maximization (MI-MAX) and divergence minimization (D-MIN) – supporting unsupervised skill learning and distribution sketching as other modes of behavior specification. In addition, we discuss how to standardize metrics for evaluating these algorithms, which can no longer rely on simple reward maximization. Our implementations build on a hardware-accelerated Brax simulator in Jax with minimal modifications, enabling behavior synthesis within minutes of training. We hope BRAXLINES can serve as an interactive toolkit for rapid creation and testing of environments and behaviors, empowering explosions of future benchmark designs and new modes of RL-driven behavior generation and their algorithmic research.

**1 Introduction**

In the current era of neural networks and high-performance computing, large and well-engineered benchmarks [26] have enabled key architectural and algorithmic breakthroughs, in computer vision [82, 78, 26, 79, 58, 59, 114], natural language processing [137, 12] and molecular biology [67]. When scaled to the extreme levels of data and computing, these innovations can train models to master an impressive range of capabilities [27, 108, 16, 109, 111, 18, 13] exhibiting developer-aware generalization [21], where the trained models can function even on datasets outside the developer’s imagination. Undoubtedly, the massive success of supervised learning (SL) has been largely due...
Figure 1: Braxlines vision: from behavior engineering to distillation. Our behavior engineering toolkit starts from Braxlines Composer, a programmatic API that facilitates environment engineering and will accelerate the proliferation of novel environments for continuous control. Components in green represent multiple modes of RL-driven behavior engineering. Red components require human inputs and, except for environment engineering, require different modes of specifications from the designers (see Table 2). Importantly, all behaviors from these modes can be aggregated and fed to downstream behavior distillation modules. We believe that maximizing simulation throughput and minimizing human inputs as the keys to scalable behavior generation, where in this work we focus on enabling MI-MAX and D-MIN as new modes of behavior engineering.

To large, diverse, and high-quality datasets, that are relatively simple to collect. In this paradigm, data generation essentially comes down to finding paired data: speech with texts [49], images with texts [26, 138, 6, 111, 109], words with words [90, 137, 27, 108, 16, 18], pixels with pixels [73, 48, 116, 134, 74]. Moreover, a significant amount of this data can be mined automatically through the web [27, 16, 109, 18] or collected relatively effortlessly with minor bottlenecks like manual human labeling [24] or slow simulation [67].

To mirror this success in RL, we may need efficient strategies for data generation. Data generation in RL [130, 95, 89, 52] is significantly more costly (than in SL), the tasks design space is infinite, and in real-world environments like robotics, healthcare, or dialog modeling [52, 70, 98, 65] data is scarce. Even simulated environments [10, 14, 131, 143, 23, 139, 121, 19, 31] are arguably far from having sufficient diversity, learnability, regularity, and downstream applicability to come close to enabling the levels of architectural breakthrough we have witnessed in SL.

Today, there exist data-centric techniques in RL such as policy distillation [117, 62, 118, 84], hindsight imitation learning or RL [85, 92, 4, 105, 70, 66, 91, 17] and offline RL [86, 42, 80, 40, 47, 128, 93] that aim to learn faster by better utilizing prior policies or experiences. Behavior distillation techniques offer an important alternative to popular approaches [10, 14, 131, 95, 124, 125, 51, 54, 41] that often require to start tabula rasa and rediscover meaningful behaviors over and over again. However, we argue that the question of how to obtain interesting and useful data for distillation methods is under-explored. Prior work [39] largely focuses on collecting human trajectories or obtaining trajectories from policies trained with engineered rewards. Both approaches are, practically and computationally, prohibitively expensive. In this paper, we focus on alternative methods to generate diverse and useful behaviors.

We introduce Braxlines, an interactive toolkit for principled behavior creation for continuous control tasks (see Figure 1) and claim the following key contributions:

- Braxlines introduces a novel programmatic API for environment composition, Braxlines Composer, that enables RL researchers to create continuous control environments from scratch or pre-defined components.
- Braxlines provides clean, minimalistic implementations for two broad families of algorithms suitable for reward-free behavior engineering: mutual information maximization (MI-MAX) and divergence minimization (D-MIN). They provide a rich set of alternative, sometimes complementary, algorithms for behavior engineering, including goal-conditioned RL [69, 122, 4,
Table 1: Run-time speeds for DIAYN [34] on Ant with different library and simulators. We adopt a recent open-source DIAYN implementation released by Zhao et al. [144] built on Baselines [29].

| Library       | Run-time | Steps       | Resource          | Simulator   | Backends           |
|---------------|----------|-------------|-------------------|-------------|--------------------|
| Baselines [29, 144] | 3.5 hours | $4.0 \times 10^7$ | 16 CPU + 1 GPU | MuJoCo      | TensorFlow, OpenMPI |
| BraxLINES     | 3.5 min  | $2.0 \times 10^8$ | 2×2 TPU (free)   | Brax        | Jax                |

105], empowerment maximization [75, 34, 20], state marginal matching and adversarial inverse RL [63, 38, 46, 83].

- The accompanying toolkit provides absolute and stationary metrics for evaluating MI-MAX and D-MIN algorithms, whose reward functions dynamically varies over training and across different implementation choices [75, 34, 20]. Some of these metrics essentially measure characteristics of behaviors themselves, such as how much control of degrees of freedom of the world an agent has, in a task-agnostic sense, providing more intrinsic insights into agent-environment interactions [136, 15].

- The open-source implementation based on the Brax [37] physics library is extremely fast, allowing interactive creation of novel behaviors in a few minutes through Google Colab on a freely available 2×2 with 8 cores TPU (see Table 1). This effectively enables real-time interactive RL-driven environment and behavior designs.

2 Related Work

Benchmarks and Baselines. Numerous benchmarks proposed over the years have spanned a wide range of tasks including simulated games of varying complexities [10, 139], continuous control and robotics [133, 131, 143, 121, 31], or procedurally generated environments [23, 132]. BraxLINES differentiate by focusing on improving the roundtrip time from conception to experimental results, increasing the interactivity of RL research. We leverage Brax [37] highly-parallellizable simulations to significantly reduce both time and computational requirements for experimentation in RL. Furthermore, using BraxLINES researchers can fix well-tested algorithmic baselines and iterate quickly over environment designs. Also, while many existing libraries [32, 105, 100, 29, 110, 88] provide fine-tuned collections of common deep RL [95] algorithms, these works focus mostly on optimizing painstakingly hand-designed rewards (see Table 5 in Appendix A) using algorithms of varying complexity, from basic [141] to more advanced techniques [89, 125, 41, 54]. In contrast, BraxLINES provides generalized implementations for mutual information maximization (MI-MAX) [20] and divergence minimization (D-MIN) algorithms [46]. While these approaches have been studied extensively [97, 50, 3, 34, 127], few benchmark implementations are available; often in isolated and not well-maintained repositories. To the best of our knowledge, we are the first to provide fast, testable, reproducible and minimalist baselines in this area (see Table 6 in Appendix A).

Reward-free Behavior Engineering. While arguably rewards are enough to produce intelligent behavior [129], reward engineering [28] bottlenecks the application of RL. Prior work have sought to address this issue by introducing other objectives such as human preferences elicitation [55, 22] or task-agnostic reward functions [123, 103, 9, 104]. On the latter, some recent works have emphasized empowerment [75, 119, 68, 97] and skills/options discovery [50, 36, 34, 140, 56, 126] through MI-MAX objectives. Choi et al. [20] connects these two areas with a variational approach to goal-conditioned RL [69, 4, 105, 106, 140]. Section 3.1 discusses how BraxLINES leverages this variational approach to implement MI-MAX algorithms. On the other hand, an alternative to generating reward-free behaviours is to learn from human demonstrations [7]. The range of techniques has spanned from feature expectation matching [101, 1], maximum entropy formulations [145, 142], to adversarial approaches to generative modelling [63, 38, 35]. Recently, unifying frameworks [46, 71] emerged under a probabilistic view, based on algorithms the minimization of $f$-divergences [115, 25] between state-action and state marginal distributions. BraxLINES leverages, as we discuss in Section 3.2, Ghasemipour et al. [46] to implement algorithms of the D-MIN family.

Metrics for Reward-Free Behavior. One limitation of reward-free approaches to RL has been the lack of quantitative evaluation metrics. Previous work in both MI-MAX [34, 3, 127, 126] and D-MIN [46, 71, 63, 38, 35] families have relied on either qualitative analysis of the learned behavior, the value of the objective (which usually saturates), and the performance on existing reward functions...
for downstream tasks. In the case of MI-MAX approaches, as mutual information is difficult to scale to high-dimensional spaces \([107, 8, 135]\), it seems particularly hard to come up with quantitative metrics. **BRAXLINES** toolkit provides a non-parametric, particle-based approximation to mutual information similar to PIC metrics \([45]\). We also leverage this approach to compute metrics for D-MIN algorithms. Finally, we provide an implementation of Latent Goal Reaching (LGR) \([20]\) that leverages the connection between goal-conditioned RL and MI-MAX objectives. We discuss this metrics further in Section 4 and contrast with prior evaluation techniques in Appendix C and Table 7.

**Comparison to Other Benchmarks** We surveyed the support of common RL algorithms in well-maintained open-source repositories of baselines: Baselines \([29]\), Stable Baselines \([110]\), RLLab \([32]\), Ti-Agents \([53]\), RLLib \([88]\), and PFRL / ChainerRL \([43]\). For each, we verified the support for continuous, reward maximization algorithms like DDPG \([89]\), ASC \([96]\), PPO \([123]\), TRPO \([124]\), TD3 \([41]\), SAC \([54]\) and ES \([120]\). Similarly, we investigated whether existing baselines provide support for algorithms of the MI-MAX and D-MIN families. With the exception of RLLab and OpenAI Baselines, there were no other benchmark implementation for MI-MAX GCRL \([69]\), DIAYN \([34]\), DISCERN \([140]\), VISR \([56]\) or D-MIN algorithms \([63, 46, 71]\). Table 5 and 6 in Appendix A show the findings of our survey. **BRAXLINES** is, to the best of our knowledge, the first reproducible and reusable open-source library of baseline implementations for reward-free RL algorithms.

### 3 Background

**Notations** We consider a Markov Decision Process (MDP) to be a tuple characterized by \((\mathcal{S}, \mathcal{A}, p, r, \rho_0, \gamma)\); state space \(\mathcal{S}\), action space \(\mathcal{A}\), transition probability \(p : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}\), reward function \(r : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}\), initial state distribution \(\rho_0\), and discount factor \(\gamma \in (0, 1]\). A policy is a function \(\pi : \mathcal{S} \rightarrow \mathcal{A}\) that defines behaviors. In this work, we denote the state-action and marginal state distribution of a policy as \(\rho_\pi(s, a)\) and \(\rho_\pi(s)\), respectively.

#### 3.1 Mutual Information Maximization (MI-MAX)

Reward-free RL typically considers the maximization of mutual information between actions and future states. Objectives such as empowerment \([75, 97]\) or unsupervised skills discovery \([50, 34, 3, 140]\) propose the maximization of mutual information between states and abstracted actions \(z \sim p(z)\) (commonly known as skills \([112]\)). Algorithms in this family learn policies \(\pi(a|s, z)\) conditioned on this latent actions. Recently, Choi et al. \([20]\) presented Variational Goal-Conditioned RL (V-GCRL), a framework that unifies Goal-Conditioned RL (GCRL) \([69]\) and a variational approach to MI-MAX, derived from the mutual information maximization objective:

\[
\max_{\pi} \text{MI}(z, s; \pi) = \max_{\pi} H(s; \pi) - H(s|z; \pi) \\
= \max_{\pi} H(z) - H(z|s; \pi) \\
= \max_{\pi} \int \int p(z) \rho_\pi(z|s) \log p_\pi(z|s) - \int p(z) \log p(z)
\]

where \(MI(z, s; \pi)\) is the mutual information between the distribution of latent actions or skills \(z \sim p(z)\) and the state marginal distribution \(s \sim \rho_\pi(s)\), under \(z\)-conditioned policy \(\pi(a|s, z)\). The objective in Eq. 1 is a generative formulation while Eq. 2 defines a discriminative of the MI-MAX objective. Due to the intractability of the true posterior \(\rho_\pi(z|s)\), a variational bound of Eq. 2 is used instead:

\[
\max_{\pi} \text{MI}(z, s; \pi) \geq \max_{\pi} \int p(z) \rho_\pi(z|s) \log q(z|s) - \int p(z) \log p(z)
\]

that enables most of the algorithms in the MI-MAX family \([69, 87, 34, 140, 56, 127]\).

#### 3.2 Divergence Minimization (D-MIN)

Inverse RL (IRL) \([101, 1]\) aims to infer the reward function and subsequently obtain an optimal policy from an expert behavior. Seminal work \([63]\) has demonstrated that the problem of MaxEnt IRL is equivalent to matching the state-action marginal of a policy, \(\rho_\pi(s, a)\), to that of the expert's \(\rho_{\text{exp}}(s, a)\). Thus, distribution-matching GAN \([48]\) techniques can be used for IRL with little expert data, leading
to Adversarial Imitation Learning (AIL) of methods [63, 38]. Recently, the work in [46, 71] have shown that to correspond to different choice of $f$-divergences for state-action distribution matching.

An interesting modification studied in [46, 83, 57] matches $\rho_{\text{target}}(s)$ to a desired distribution $\rho^*(s)$ and allows AIL to match behavior not necessarily generated by an expert policy, and can even be designed without any access to the underlying MDP. For a given choice of $f$-divergence, minimizing $D_f$ of state marginals can be accomplished through an adversarial optimization setup [46].

$$\min_{\pi} D_f(\rho^*(s), \rho_{\text{target}}(s)) = \max_{\pi} E_{\rho^*(s)} \left[ f^* (T_\omega(s)) \right] = \max_{\pi} E_{\rho^*(s)} \left[ r^* (s) \right]$$

recovering optimization objectives similar to GAIL [63] (Jensen-Shannon divergence), AIRL [38] (reverse KL divergence), and F-AIRL [46] (forward KL divergence).

In these settings, the discriminator is a binary classifier distinguishing between target states and states visited by the policy, trained using cross entropy. The reward functions for training the policy are obtained from:

$$r_{\text{GAIL}}(s) := \log D(s) = \log \rho_{\text{target}}(s) - \log (\rho_{\text{target}}(s) + \rho^*(s))$$

$$h(s) := \log D(s) - \log (1 - D(s))$$

$$r_{\text{AIRM}}(s) := h(s) = \log \rho_{\text{target}}(s) - \log \rho^*(s)$$

$$r_{\text{MLE}}(s) := \log \rho_{\text{target}}(s).$$

where $D(s)$ is the probability the discriminator assigns for $s$ being from the target distribution. For a more in depth discussion, we refer the reader to [46, 71].

4 Tools for Behavior Engineering

RAXLINES for behavior engineering is built over three pillars: (1) an environments composer, (2) a set of stable baselines, and (3) a collection of metrics for reward-free behavior evaluation.

4.1 RAXLINES Composer

COMPOSER is designed for modularity and reusability. Figure 2 illustrates examples of environments that can be composed easily using COMPOSER. See Appendix D for an Ant Push task example constructed under 50 lines. Since all observations, reward functions, and scene components can be combined and reused, COMPOSER allows programmatic procedural generation of parameterized environments. Combined with BRAK’s PPO/ES methods and RAXLINES’ MI-MAX/D-MIN implementations that allow training within minutes, these enable designers to quickly design, debug, and tune tasks.

4.2 Stable Baselines for Reward-Free Behavior Generation

RAXLINES is designed to optimize for speed and minimalism of algorithms in the MI-MAX and D-MIN families. Prior implementations [34, 63, 38, 46, 83, 99] rely on heavily modifying different RL optimizers (e.g. SAC [54], TD3 [41], PPO [125], MPO [2]), making comparative analyses and code reuses difficult. The benchmark implementations we provide are unified under Brax’s PPO [37], enabling stable and speedy training on medium-size problems within minutes. Table 1 shows RAXLINES speed gains of orders of magnitude compared to existing DIAYN [34] baselines. Furthermore, we leverage recent unification papers [46, 20] to keep RAXLINES design as clean and minimal as possible. A minimalistic approach to RL [40] ensures that codebases does not rely on extensive hyperparameter designs [60, 5, 33, 44], and can be debugged, reproduced, extended, and mixed easily downstream.

We present in Table 2 an analysis of the flexibility of RAXLINES using an algorithm-implementation decomposition similar to Furuta et al. [44] that separates algorithm (i.e., mathematical and algorithmic choices) from implementation details (i.e., implementation and code-level optimizations). In

---

1The last reward Eq. 7 is technically not an instance of D-MIN algorithms and is a plain stationary reward function, but it is effectively AIRL(Eq. 6) without $H^N(s)$ term. In Figure 4, we show that sometimes this presents competitive results for matching multi-modal distribution as a full D-MIN algorithm.
Figure 2: BRAXLINES COMPOSER API is a flexible and fast environment engineering tool for continuous control. The space of environments designs spans from (left) goal-based locomotion + manipulation task, (middle) parameterized morphologies, to (right) multi-agent systems. See Appendix D for an example on how to construct Ant Push (left) in under 50 lines of code.

| Algorithm | Family | Implementation | User Specification |
|-----------|--------|----------------|--------------------|
| GCRL [69, 4, 105, 20] | MI-MAX | Fix \( q(z|s) = \mathcal{N}(o(s), \sigma f), p(z) + \text{Offset} \) | \( p(z), o(\cdot) \) |
| V-GCRL [20, 34, 140, 56] | MI-MAX | Param \( q_0(z|o(s)) + \text{Fix} p(z) + \text{SN + Offset} \) | \( o(\cdot), p^{\text{true}}(o(s)) \) |
| GAIL [63] | D-MIN | Eq. 5 + Offset | \( o(\cdot), o^{\text{true}}(o(s)) \) |
| AIRL [38] | D-MIN | Eq. 6 + Offset | \( o(\cdot), o^{\text{true}}(o(s)) \) |

Table 2: A summary of example BRAXLINES algorithms explained in terms of the Algorithm Family/Implementation decomposition in [44]. BRAXLINES emphasizes on minimal implementations with little to no code-level optimization (only spectral normalization (“SN”) [94, 20] on discriminator \( q_0(z|\cdot) \)) and adding positive constant offsets (“Offset”), equivalent survival bonus, to ensure that rewards almost always positive (see Appendix A.1). User Specification lists what BRAXLINES users are required to define to perform feature engineering \( o(\cdot) \), and marginal state distribution matching \( \rho^{\text{true}}(\cdot) \). Importantly, since V-GCRL has representation learning capacity, \( p(z) \) can often be simply a fixed uninformative prior, e.g. zero-mean Gaussian or a uniform Categorial [34, 20].

addition, we define what are users required to specify to turn a family of algorithms into a concrete instance (e.g., MI-MAX to DIAYN). In the sections that follow, we present more detailed explanations of both MI-MAX and D-MIN families, and how are they supported in BRAXLINES. We support flexible parametrizations of \( q(z|s) \) that could take the form of an isotropic Gaussian distribution \( q(z|s) = \mathcal{N}(O; \mu, \sigma^2 I) \) or a parametric tractable posterior \( q_\theta(z|s) \) learned using function approximation (i.e., neural networks). Similarly, BRAXLINES provides baseline implementations for variations of the AIL family of algorithms. In the case of D-MIN algorithms, we provide the flexibility for users to specify feature engineering functions as well as behavior distributions over this feature space. Together, algorithms in both families are a key ingredient for generating diverse behaviors through little human intervention.

4.3 Metrics

Both MI-MAX and D-MIN algorithms infer dynamic reward functions during learning (except in few special cases like GCRL), which can change arbitrarily across training iterations, as well as across different implementation and hyperparameter choices (e.g. discrete or continuous \( z \)-space in MI-MAX, or different choices of reward transformation in D-MIN as in Table 2). This makes episodic rewards inapplicable for quantitatively evaluating optimization convergence or final performances. Common alternatives are also limited and hard to automate: MI-MAX algorithms often use qualitative visual inspections or down-stream task performances [34, 127, 126], while D-MIN algorithms mostly focus on imitation learning and frequently use task rewards directly to compare how close to the experts they got [63, 38, 46].

Inspired by prior works [20], we provide objective metrics for MI-MAX and D-MIN, that (1) provide an intuitive and interpretable absolute units of performance measure applicable to any algorithm instance within the same family, and (2) are stationary throughout learning, meaning that they do
not depend of quantities that change over the course of training or across runs of an experiment (such as rewards given by the discriminator).

### 4.3.1 MI-MAX Metrics

We implemented two metrics for evaluating the behaviors generated by algorithms in the MI-MAX family that leverage approximations to mutual information. These metrics compute, in general, how much an agent learned to control each dimension of the environment.

**Particle-based Mutual Information Approximation.** We can directly adopt similar techniques in Furuta et al. [45] to estimate empowerment of a trained policy. It uses straight-forward discretization for tractable non-parametric estimation in 1D and 2D. Intuitively this metric quantifies how much predictive control over each dimension(s) of the environment an agent has learned, a direct measure of the original MI-MAX objective in Eq. 1 (without variational approximation). Note that reliable mutual information estimation in high dimensions is still an actively researched problem, but some scalable estimation techniques [107, 8, 135] will be added later.

**Algorithm 1: Particle-based Mutual Information Approximation**

**Input:** agent $\pi(a|s, z)$; intent $p(z)$; feature function $o(s)$; bin size $B$; bin range $(a, b)$

**Output:** Mutual information estimate $MI$

For $n = 1, \ldots, N$ do

- Sample $z_n \sim p(z)$ // Sample an agent intent
- Sample $s_{n,m,t} \sim \pi(s|z_n)$ // Collect $M$ episodes of horizon $T$ for $z_n$
- // Estimate conditional entropy in $o$-space for $z_n$ using np.histogram($2d(B, (a, b))$
- Estimate $h_n$ with $p(o|z_n) \approx \frac{1}{MT} \sum_{m,t} \delta(o = o(s_{n,m,t}))$

end

// Estimate marginal entropy in $o$-space for $z_n$ using np.histogram($2d(B, (a, b))$
Estimate $h$ with $p(o) \approx \frac{1}{NMT} \sum_{n,m,t} \delta(o = o(s_{n,m,t}))$

$MI = h - \frac{1}{N} \left( \sum_n h_n \right)$ // Compute MI estimate

**Latent Goal Reaching.** In our experiments, we fixed $N = 1$ for Algorithm 3 and use the deterministic sampling (for Gaussians, take the mean; for Categoricals, take the argmax). LGR for GCRL in Section 3.1 corresponds exactly to the standard goal-reaching reward evaluation. While the LGR metric in Algorithm 3 (see Appendix B) is motivated intuitively as a task-oriented metric from GCRL [20] and appears unrelated to the MI-MAX objective (Eq. 2) or its approximation (Algorithm 1), it can also be viewed as a crude approximation to MI, as we show in Appendix B.1.

### 4.3.2 D-MIN Metrics

**Particle-based Divergence Approximation.** For lower dimension cases, we use the energy distance for non-parametric estimation. Given two distributions $p$ and $q$, the energy distance is defined as,

$$d(p, q) := 2E_{x \sim p, y \sim q} ||x - y|| - E_{x,x' \sim p} ||x - x'|| - E_{y,y' \sim q} ||y - y'||$$

where $|| \cdot ||$ is the Euclidean norm but may be any desired metric. For higher dimensional and more complex distributions, adhoc notions of distance (such as Frechet Inception Distance [61]) have been proposed.

**Algorithm 2: Energy Distance**

**Input:** agent $\pi(a|s); o(s)$; target samples $o_{1:L}^{target} = o(s_{1:L}^{target}) \sim p^{target}(s)$

**Output:** Energy distance estimate $D$

Sample $o_{m,t}^{\text{target}} = o(s_{m,t}^{\text{target}}), s_{m,t} \sim \pi$ in $\mu$ // Collect $M$ episodes of horizon $T$

// Compute energy distance

$$D = \frac{2}{MT} \sum_{m,t} \delta(o_{m,t}^{\text{target}} - o_{m,t}) - \frac{1}{MT} \sum_{m,t,m',t'} ||o_{m,t} - o_{m',t'}^{\text{target}}|| - \frac{1}{2} \sum_{t'} \delta(o_{t}^{\text{target}} - o_{t}')$$
We provide both illustrative Google Colab examples for interactive environment composition and training, and a set of quantitative benchmark results that could accelerate future algorithmic research in MI-MAX and D-MIN RL. Importantly, due to two orders of training speedups as measured in Table 1, a medium-size environment can be composed and trained in a few minutes on Google Colab with 2×8 cores TPU, enabling interactive environment designs and algorithm deployments. All BRAXLINES codes, documentation, result videos, and Colab examples are accessible at https://github.com/google/brax/tree/main/brax/experimental/braxlines. Experimental details and hyperparameters, additional benchmark results, and ablation studies are available in Appendix A.

### 5 Experiments

MI-MAX Figure 3 shows the training curves with respect to (a) inferred reward, (b, c) mutual information MI and state entropy $H(s)$ estimates, and (d) LGR estimate. The scales of reward between cDIAYN (continuous DIAYN)/GCR and DIAYN are very different due to the continuous and discrete $z$ respectively, and they also vary non-monotonically during training due to the interplay between RL and discriminator fitting. In contrast, both MI and LGR estimates have the same comparable absolute units for any algorithm in the family, making them possible for estimating the effectiveness of learning and compare algorithmic performances. Additional results are presented in Table 3 and Appendix A.2.

D-MIN Similarly to Figure 3, Figure 4 (left) presents the training curves for reward and divergence estimate. Unsurprisingly, while the reward discriminator loss curves are incomparable, the energy distance estimate curve can be reliably used to measure convergence and compare which algorithmic

---

Table 3: Benchmark for MI-MAX algorithms averaged over 10 seeds.

| Environment   | MI-MAX algo. | MI($s, z$)   | $H(s)$       | -LGR    |
|---------------|--------------|--------------|--------------|---------|
| HalfCheetah   | DIAYN        | 1.815 ± 0.201 | 5.164 ± 0.455 | −0.492 ± 0.154 |
| HalfCheetah   | DIAYN_FULL   | 0.490 ± 0.156 | **5.519 ± 0.178** | −1.397 ± 0.287 |
| HalfCheetah   | GCR          | 1.626 ± 0.157 | 5.307 ± 0.173 | −0.293 ± 0.356 |
| HalfCheetah   | cDIAYN       | 1.571 ± 0.098 | 5.104 ± 0.353 | −0.741 ± 0.365 |
| Ant           | DIAYN        | 1.113 ± 0.268 | 5.588 ± 0.286 | −2.280 ± 0.539 |
| Ant           | DIAYN_FULL   | 0.034 ± 0.066 | 5.044 ± 0.639 | −3.010 ± 0.010 |
| Ant           | GCR          | **1.218 ± 0.192** | **6.066 ± 0.051** | **−2.074 ± 0.232** |
| Ant           | cDIAYN       | 0.750 ± 0.185 | 5.253 ± 0.270 | −2.885 ± 0.291 |
| Humanoid      | DIAYN        | **0.927 ± 0.128** | **6.074 ± 0.088** | **−2.313 ± 0.266** |
| Humanoid      | DIAYN_FULL   | 0.071 ± 0.007 | 5.676 ± 0.081 | −3.051 ± 0.028 |
| Humanoid      | GCR          | 0.769 ± 0.146 | 6.058 ± 0.063 | −2.755 ± 0.115 |
| Humanoid      | cDIAYN       | 0.297 ± 0.147 | 5.677 ± 0.060 | −2.738 ± 0.112 |

2XY velocities correspond to dimensions (13, 14) of Ant env. Since each dimension had similar MI estimates, we only show for MI and entropies for dim= (13, ). See Appendix A.1 for more discussions.

3If you enable dense evaluations of the quantitative metrics in Section 4, it could slow down to 10-20 minutes, but we mainly recommend these during initial debugging or full quantitative benchmarking.
Table 4: Benchmark for D-MIN algorithms averaged over 10 seeds.

| Environment  | D-MIN algo. | Energy Distance |
|--------------|-------------|-----------------|
| HalfCheetah  | AIRL        | -1.448 ± 0.843  |
| HalfCheetah  | GAIL        | -0.516 ± 0.640  |
| HalfCheetah  | GAIL2       | -2.488 ± 0.355  |
| HalfCheetah  | MLE         | -2.614 ± 0.415  |
| Ant          | AIRL        | -2.388 ± 1.194  |
| Ant          | GAIL        | -0.802 ± 0.460  |
| Ant          | GAIL2       | -2.808 ± 0.946  |
| Ant          | MLE         | -1.829 ± 0.573  |
| Humanoid     | AIRL        | -1.122 ± 0.210  |
| Humanoid     | GAIL        | -1.790 ± 0.413  |
| Humanoid     | GAIL2       | -1.471 ± 0.528  |
| Humanoid     | MLE         | -2.037 ± 0.973  |

Figure 4: D-MIN results for Ant averaged over 10 seeds: (from left to right) (a, b) episode reward and energy distance metric across training iterations; (c, d) visualizations of learned policy state marginal distribution and the target. Similarly to Figure 3 of MI-MAX, (a) shows that episode rewards cannot be used as a metric for evaluating learning progress within each run or across runs of different choices. Our proposed metric (b), however, can successfully measure the convergence and algorithm performances (GAIL has lowest energy distance and performs the best). (c) shows the result of matching a bi-modal distribution in XY velocity space, where the Ant acquired a hopping behavior.

variant performs the best in terms of state-marginal matching. Additional results are presented in Table 4 and Appendix A.2.

Limitations

- **Feature Engineering and Metric Space Assumption**: Both MI-MAX and D-MIN objectives indirectly involve density estimation, which is sensitive to high dimensionality and poor conditioning. An implicit assumption in all the above metrics is that \( o(s) \) by the user specifies a low-dimensional, good metric space where Euclidean distance is a good measure for proximity. Since our emphasis is on behavior generation in simulation with access to simulator states (which could be used by downstream behavior distillation procedures [84, 92]), this remains a reasonable assumption in many cases.

- **Sample Efficiency**: Sample efficiencies are not the primary concern for BRAXLINES, as the code is designed to maximize the benefits of hardware-accelerated simulations and serve as an interactive toolkit for behavior designers and RL researchers exploring high-level concepts. While these are not tuned with respect to sample efficiency compared to many prior works [126], they exhibit orders of magnitudes speedups in training and often better final performances (e.g. DIAYN on Humanoid has not been successful [34, 127, 20]).

6 Conclusion

In this paper, we introduced BRAXLINES, a fast and interactive toolkit for behavior synthesis beyond reward engineering in continuous control that unlocks four key bottlenecks in RL research: (i) fast environment generation, (ii) difficulty and limitations of reward engineering, (iii) slow iteration speeds, and (iv) lack of metrics on data or tasks properties. Our experimental analysis showcased how two families of algorithms – mutual information maximization (MI-MAX) and divergence minimization (D-MIN) – can generate interesting behaviors in continuous control environments, and provided concrete evaluation metrics for interactive debugging. We expect that these approaches,
complementary with classical behavior generation techniques through reward engineering would be useful for the long-term goal of creating large data sets of interesting behaviors, and enable algorithmic and architectural breakthrough in RL. In turn, more diverse data sets of behaviors have the potential to enable more efficient algorithms (e.g. via distillation) for few-shot learning in reinforcement learning, as recently observed in supervised learning.

Acknowledgments and Disclosure of Funding

We appreciate feedback and advice from Sergey Levine, Nicolas Heess, Marc Bellemare, Yutaka Matsuo, Pierre Sermanet, Douglas Eck, and Vincent Vanhoucke.

References

[1] Pieter Abbeel and Andrew Y Ng. Apprenticeship learning via inverse reinforcement learning. In *International Conference on Machine Learning*, 2004.

[2] Abbas Abdolmaleki, Jost Tobias Springenberg, Yuval Tassa, Remi Munos, Nicolas Heess, and Martin Riedmiller. Maximum a posteriori policy optimisation. In *International Conference on Learning Representations*, 2018.

[3] Joshua Achiam, Harrison Edwards, Dario Amodei, and Pieter Abbeel. Variational option discovery algorithms. *arXiv preprint arXiv:1807.10299*, 2018.

[4] Marcin Andrychowicz, Filip Wolski, Alex Ray, Jonas Schneider, Rachel Fong, Peter Welinder, Bob McGrew, Josh Tobin, Pieter Abbeel, and Wojciech Zaremba. Hindsight experience replay. In *Advances in neural information processing systems*, 2017.

[5] Marcin Andrychowicz, Anton Raichuk, Piotr Stańczyk, Manu Orsini, Sertan Girgin, Raphaël Marinier, Leonard Hussenot, Matthieu Geist, Olivier Pietquin, Marcin Michalski, Sylvain Gelly, and Olivier Bachem. What matters for on-policy deep actor-critic methods? a large-scale study. In *International Conference on Learning Representations*, 2021.

[6] Stanislaw Antol, Aishwarya Agrawal, Jiasen Lu, Margaret Mitchell, Dhruv Batra, C. Lawrence Zitnick, and Devi Parikh. VQA: Visual Question Answering. In *International Conference on Computer Vision*, 2015.

[7] Brenna D Argall, Sonia Chernova, Manuela Veloso, and Brett Browning. A survey of robot learning from demonstration. *Robotics and autonomous systems*, 2009.

[8] Mohamed Ishmael Belghazi, Aristide Baratin, Sai Rajeswar, Sherjil Ozair, Yoshua Bengio, Aaron Courville, and Devon Hjelm. Mutual information neural estimation. In *International Conference on Machine Learning*, 2018.

[9] Marc Bellemare, Sriram Srinivasan, Georg Ostrovski, Tom Schaul, David Saxton, and Remi Munos. Unifying count-based exploration and intrinsic motivation. In *Advances in neural information processing systems*, 2016.

[10] Marc G. Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 2013.

[11] Glen Berseth, Daniel Geng, Coline Devin, Nicholas Rhinehart, Chelsea Finn, Dinesh Jayaraman, and Sergey Levine. Smirl: Surprise minimizing reinforcement learning in unstable environments. In *International Conference on Learning Representations*, 2021.

[12] Ondrej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, Radu Soricut, Lucia Specia, and Aleš Štajnman. Findings of the 2014 workshop on statistical machine translation. In *Workshop on Statistical Machine Translation*, 2014.

[13] Rishi Bommasani, Drew A. Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S. Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, Erik Brynjolfsson, Shyamal Buch, Dallas Card, Rodrigo Castellon, Niladri Chatterji, Annie Chen, Kathleen Creel, Jared Quincy Davis, Dora Demszy, Chris Donahue, Moussa Doumbouya, Esin Durmus, Stefano Ermon, John Etchemendy, Kaiwen Ethayarajh, Li Fei-Fei, Chelsea Finn, Trevor Gale, Lauren Gillespie, Karan Goel, Noah Goodman, Shelby Grossman, Neel Guha, Tatsunori Hashimoto, Peter Henderson, John Hewitt, Daniel E. Ho, Jenny
Hong, Kyle Hsu, Jing Huang, Thomas Icard, Saahil Jain, Dan Jurafsky, Pratyusha Kalluri, Siddharth Karamcheti, Geoff Keeling, Fereshte Khani, Omar Knattab, Pang Wei Koh, Mark Krass, Ranjay Krishna, Rohith Kuditipudi, Ananya Kumar, Faisal Ladhak, Mina Lee, Tony Lee, Jure Leskovec, Isabelle Levent, Xiang Li, Yuechen Li, Tengyu Ma, Ali Malik, Christopher D. Manning, Suvin Mirchandani, Eric Mitchell, Zanele Munyikwa, Suraj Nair, Avamika Narayan, Deepak Narayanan, Ben Newman, Allen Nie, Juan Carlos Niebles, Hamed Nilloforosh, Julian Nyarko, Giray Ogun, Laureal Orr, Isabel Papadimitriou, Joon Sung Park, ChrisPiech, Eva Portelance, Christopher Potts, Aditi Raghunathan, Rob Reich, Hongyu Ren, Frieda Rong, Yusuf Roohani, Camilo Ruiz, Jack Ryan, Christopher Ré, Dorsa Sadigh, Shiori Sagawa, Keshav Santhanam, Andy Shih, Krishnan Srinivasan, Alex Tamkin, Rohan Taori, Armin W. Thomas, Florian Tramèr, Rose E. Wang, William Wang, Bohan Wu, Jiajun Wu, Yuhuai Wu, Sang Michael Xie, Michihiro Yasunaga, Jiaxuan You, Matei Zaharia, Michael Zhang, Tianyi Zhang, Xikun Zhang, Yuhui Zhang, Lucia Zheng, Kaitlyn Zhou, and Percy Liang. On the opportunities and risks of foundation models. arXiv preprint arXiv:2108.07258, 2021.

[14] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym. arXiv preprint arXiv:1606.01540, 2016.

[15] Rodney A. Brooks. Intelligence without representation. Artificial Intelligence, 1991.

[16] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. Language models are few-shot learners. arXiv preprint arXiv:2005.14165, 2020.

[17] Yevgen Chebotar, Karol Hausman, Yao Lu, Ted Xiao, Dmitry Kalashnikov, Jake Varley, Alex Irpan, Benjamin Eysenbach, Ryan Julian, Chelsea Finn, and Sergey Levine. Actionable models: Unsupervised offline reinforcement learning of robotic skills. arXiv preprint arXiv:2104.07749, 2021.

[18] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolai Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. Evaluating large language models trained on code. arXiv preprint arXiv:2107.03374, 2021.

[19] Maxime Chevalier-Boisvert, Lucas Willems, and Suman Pal. Minimalistic gridworld environment for openai gym. https://github.com/maximecb/gym-minigrid, 2018.

[20] Jongwook Choi, Archit Sharma, Honglak Lee, Sergey Levine, and Shixiang Shane Gu. Variational empowerment as representation learning for goal-based reinforcement learning. In International Conference on Machine Learning, 2021.

[21] François Chollet. On the measure of intelligence. arXiv preprint arXiv:1911.01547, 2019.

[22] Paul F Christiano, Jan Leike, Tom B Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. In Advances in neural information processing systems, 2017.

[23] Karl Cobbe, Christopher Hesse, Jacob Hilton, and John Schulman. Leveraging procedural generation to benchmark reinforcement learning. arXiv preprint arXiv:1912.01588, 2020.

[24] Kevin Crowston. Amazon Mechanical Turk: A Research Tool for Organizations and Information Systems Scholars, pages 210–221. Springer, 2012.

[25] Imre Csiszar. Information-type measures of difference of probability distributions and indirect observation. Studia Scientiarum Mathematicarum Hungarica, 1967.

[26] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In Conference on Computer Vision and Pattern Recognition, 2009.
[27] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2019.

[28] Daniel Dewey. Reinforcement learning and the reward engineering principle, 2014.

[29] Prafulla Dhariwal, Christopher Hesse, Oleg Klimov, Alex Nichol, Matthias Plappert, Alec Radford, John Schulman, Szymon Sidor, Yuhuai Wu, and Peter Zhokhov. Openai baselines. https://github.com/openai/baselines, 2017.

[30] Kien Do and Truyen Tran. Theory and evaluation metrics for learning disentangled representations. In International Conference on Learning Representations, 2020.

[31] Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. Carla: An open urban driving simulator. In Conference on Robot Learning, 2017.

[32] Yan Duan, Xi Chen, Rein Houthooft, John Schulman, and Pieter Abbeel. Benchmarking deep reinforcement learning for continuous control. In International conference on machine learning, 2016.

[33] Logan Engstrom, Andrew Ilyas, Shibani Santurkar, Dimitris Tsipras, Firdaus Janoos, Larry Rudolph, and Aleksander Madry. Implementation matters in deep rl: A case study on ppo and trpo. In International Conference on Learning Representations, 2019.

[34] Benjamin Eysenbach, Abhishek Gupta, Julian Ibarz, and Sergey Levine. Diversity is all you need: Learning diverse skills without a reward function. In international conference on learning representations, 2019.

[35] Chelsea Finn, Paul F. Christiano, Pieter Abbeel, and Sergey Levine. A connection between generative adversarial networks, inverse reinforcement learning, and energy-based models. arXiv preprint arXiv:1611.03852, 2016.

[36] Carlos Florensa, Yan Duan, and Pieter Abbeel. Stochastic neural networks for hierarchical reinforcement learning. In International Conference on Learning Representations, 2017.

[37] C. Daniel Freeman, Erik Frey, Anton Raichuk, Sertan Girgin, Igor Mordatch, and Olivier Bachem. Brax - a differentiable physics engine for large scale rigid body simulation, 2021. URL http://github.com/google/brax.

[38] Justin Fu, Katie Luo, and Sergey Levine. Learning robust rewards with adversarial inverse reinforcement learning. In International Conference on Learning Representations, 2018.

[39] Justin Fu, Aviral Kumar, Ofir Nachum, George Tucker, and Sergey Levine. D4RL: datasets for deep data-driven reinforcement learning. arXiv preprint arXiv:2004.07219, 2020.

[40] Scott Fujimoto and Shixiang Shane Gu. A minimalist approach to offline reinforcement learning. arXiv preprint arXiv:2106.06860, 2021.

[41] Scott Fujimoto, Herke van Hoof, and David Meger. Addressing function approximation error in actor-critic methods. In International Conference on Machine Learning, 2018.

[42] Scott Fujimoto, David Meger, and Doina Precup. Off-policy deep reinforcement learning without exploration. In International Conference on Machine Learning, 2019.

[43] Yasuhiro Fujita, Prabhat Nagarajan, Toshiaki Kataoka, and Takahiro Ishikawa. Chainerrl: A deep reinforcement learning library. Journal of Machine Learning Research, 2021.

[44] Hiroki Furuta, Tadashi Kozuno, Tatsuya Matsushima, Yutaka Matsuo, and Shixiang Shane Gu. Co-adaptation of algorithmic and implementational innovations in inference-based deep reinforcement learning. arXiv preprint arXiv:2103.17758, 2021.

[45] Hiroki Furuta, Tatsuya Matsushima, Tadashi Kozuno, Yutaka Matsuo, Sergey Levine, Ofir Nachum, and Shixiang Shane Gu. Policy information capacity: Information-theoretic measure for task complexity in deep reinforcement learning. In International Conference on Machine Learning, 2021.

[46] Seyed Kamyar Seyed Ghasemipour, Richard Zemel, and Shixiang Gu. A divergence minimization perspective on imitation learning methods. In Conference on Robot Learning, 2020.

[47] Seyed Kamyar Seyed Ghasemipour, Dale Schuurmans, and Shixiang Shane Gu. Emaq: Expected-max q-learning operator for simple yet effective offline and online rl. In International Conference on Machine Learning, 2021.
[48] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks. In Advances in neural information processing systems, 2014.

[49] Alex Graves, Abdel rahman Mohamed, and Geoffrey Hinton. Speech recognition with deep recurrent neural networks. In International Conference on Acoustics, Speech, and Signal Processing, 2013.

[50] Karol Gregor, Danilo Jimenez Rezende, and Daan Wierstra. Variational intrinsic control. arXiv preprint arXiv:1611.07507, 2016.

[51] Shixiang Gu, Timothy Lillicrap, Ilya Sutskever, and Sergey Levine. Continuous deep q-learning with model-based acceleration. In International Conference on Machine Learning, 2016.

[52] Shixiang Gu, Ethan Holly, Timothy Lillicrap, and Sergey Levine. Deep reinforcement learning for robotic manipulation with asynchronous off-policy updates. In International Conference on Robotics and Automation, 2017.

[53] Sergio Guadarrama, Anoop Korattikara, Oscar Ramirez, Pablo Castro, Ethan Holly, Sam Fishman, Ke Wang, Ekaterina Gonina, Neal Wu, Efi Kokioptoulou, Luciano Sbaiz, Jamie Smith, Gábor Bartók, Jesse Berent, Chris Harris, Vincent Vanhoucke, and Eugene Brevdo. TF-Agents: A library for reinforcement learning in tensorflow. https://github.com/tensorflow/agents, 2018.

[54] Tuomas Haarnoja, Aurick Zhou, Pieter Abbeel, and Sergey Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In International Conference on Machine Learning, 2018.

[55] Dylan Hadfield-Menell, Smitha Milli, Pieter Abbeel, Stuart Russell, and Anca D Dragan. Inverse reward design. In Advances in neural information processing systems, 2017.

[56] Steven Hansen, Will Dabney, Andre Barreto, Tom Van de Wiele, David Warde-Farley, and Volodymyr Mnih. Fast Task Inference with Variational Intrinsic Successor Features. In International Conference on Learning Representations, 2020.

[57] Elad Hazan, Sham M. Kakade, Karan Singh, and Abby Van Soest. Provably efficient maximum entropy exploration. In International Conference on Machine Learning, 2019.

[58] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In Conference on Computer Vision and Pattern Recognition, 2016.

[59] Kaiming He, Georgia Gkioxari, Piotr Dollar, and Ross Girshick. Mask r-cnn. In International Conference on Computer Vision, 2017.

[60] Peter Henderson, Riashat Islam, Philip Bachman, Joelle Pineau, Doina Precup, and David Meger. Deep reinforcement learning that matters. In AAAI conference on artificial intelligence, 2018.

[61] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. Advances in neural information processing systems, 30, 2017.

[62] Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. Distilling the knowledge in a neural network. arXiv preprint arXiv:1503.02531, 2015.

[63] Jonathan Ho and Stefano Ermon. Generative adversarial imitation learning. In Advances in neural information processing systems, 2016.

[64] Wenlong Huang, Igor Mordatch, and Deepak Pathak. One policy to control them all: Shared modular policies for agent-agnostic control, 2020.

[65] Natasha Jaques, Judy Hanwen Shen, Asma Ghandeharioun, Craig Ferguson, Agata Lapedriza, Noah Jones, Shixiang Gu, and Rosalind Picard. Human-centric dialog training via offline reinforcement learning. In Conference on Empirical Methods in Natural Language Processing, 2020.

[66] Yiding Jiang, Shixiang Gu, Kevin Murphy, and Chelsea Finn. Language as an abstraction for hierarchical deep reinforcement learning. In Advances in neural information processing systems, 2019.
John Jumper, Richard Evans, Alexander Pritzel, Tim Green, Michael Figurnov, Olaf Ronneberger, Kathryn Tunyasuvunakool, Russ Bates, Augustin Žídek, Anna Potapenko, Alex Bridglan, Clemens Meyer, Simon A A Kohl, Andrew J Ballard, Andrew Cowie, Bernardojo Romera-Paredes, Stanislaw Nikolov, Rishub Jain, Jonas Adler, Trevor Back, Stig Petersen, David Reimann, Ellen Clancy, Michal Zielinski, Martin Steinegger, Michalina Pacholska, Tamas Berghammer, Sebastian Bodenstein, David Silver, Oriol Vinyals, Andrew W Senior, Koray Kavukcuoglu, Pushmeet Kohli, and Demis Hassabis. Highly accurate protein structure prediction with AlphaFold. *Nature*, 2021.

Tobias Jung, Daniel Polani, and Peter Stone. Empowerment for continuous agent—environment systems. *Adaptive behavior*, 2011.

Leslie Pack Kaelbling. Learning to achieve goals. In *International Joint Conference on Artificial Intelligence*, 1993.

Dmitry Kalashnikov, Alex Irpan, Peter Pastor, Julian Ibarz, Alexander Herzog, Eric Jang, Deirdre Quillen, Ethan Holly, Mrinal Kalakrishnan, Vincent Vanhoucke, and Sergey Levine. QT-Opt: Scalable deep reinforcement learning for vision-based robotic manipulation. In *Conference on Robot Learning*, 2018.

Liyiming Ke, Sanjiban Choudhury, Matt Barnes, Wen Sun, Gilwoo Lee, and Siddhartha Srinivasa. Imitation learning as f-divergence minimization. In Steven M. LaValle, Ming Lin, Timo Ojala, Dylan Shell, and Jingjin Yu, editors, *Algorithmic Foundations of Robotics*. Springer, 2021.

Jackyeom Kim, Seohong Park, and Gunhee Kim. Unsupervised skill discovery with bottleneck option learning. In *International Conference on Machine Learning*, 2021.

Diederik P Kingma and Max Welling. Auto-encoding variational bayes. In *International Conference on Learning Representations*, 2014.

Diederik P. Kingma, Tim Salimans, Rafal Jozefowicz, Xi Chen, Ilya Sutskever, and Max Welling. Improving variational inference with inverse autoregressive flow. In *Advances in neural information processing systems*, 2016.

A.S. Klyubin, D. Polani, and C.L. Nehaniv. Empowerment: a universal agent-centric measure of control. In *IEEE Congress on Evolutionary Computation*, 2005.

Ilya Kostrikov. Pytorch implementations of reinforcement learning algorithms. [https://github.com/ikostrikov/pytorch-a2c-ppo-acktr-gail](https://github.com/ikostrikov/pytorch-a2c-ppo-acktr-gail), 2018.

Ilya Kostrikov, Kumar Krishna Agrawal, Debidatta Dwibedi, Sergey Levine, and Jonathan Tompson. Discriminator-actor-critic: Addressing sample inefficiency and reward bias in adversarial imitation learning. In *International Conference on Learning Representations*, 2019.

Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. Cifar-10 (canadian institute for advanced research), 2010. URL [http://www.cs.toronto.edu/~kriz/cifar.html](http://www.cs.toronto.edu/~kriz/cifar.html).

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems*, 2012.

Aviral Kumar, Aurick Zhou, George Tucker, and Sergey Levine. Conservative q-learning for offline reinforcement learning. In *Advances in Neural Information Processing Systems*, 2020.

Vitaly Kurin, Maximilian Igl, Tim Rocktäschel, Wendelin Boehmer, and Shimon Whiteson. My body is a cage: the role of morphology in graph-based incompatible control, 2021.

Yann LeCun, Corinna Cortes, and CJ Burges. Mnist handwritten digit database. *ATT Labs [Online]. Available: http://yann.lecun.com/exdb/mnist*, 2010.

Lisa Lee, Benjamin Eysenbach, Emilio Parisotto, Eric Xing, Sergey Levine, and Ruslan Salakhutdinov. Efficient exploration via state marginal matching. *arXiv preprint arXiv:1906.05274*, 2020.

Sergey Levine, Chelsea Finn, Trevor Darrell, and Pieter Abbeel. End-to-end training of deep visuomotor policies. *arXiv preprint arXiv:1504.00702*, 2016.

Sergey Levine, Peter Pastor, Alex Krizhevsky, and Deirdre Quillen. Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *arXiv preprint arXiv:1603.02199*, 2016.

Sergey Levine, Aviral Kumar, George Tucker, and Justin Fu. Offline reinforcement learning: Tutorial, review, and perspectives on open problems. *arXiv preprint arXiv:2005.01643*, 2020.
[87] Yunzhu Li, Jiaming Song, and Stefano Ermon. Infogail: Interpretable imitation learning from visual demonstrations. In Advances in neural information processing systems, 2017.

[88] Eric Liang, Richard Liaw, Robert Nishihara, Philipp Moritz, Roy Fox, Joseph Gonzalez, Ken Goldberg, and Ion Stoica. Ray rllib: A composable and scalable reinforcement learning library. arXiv preprint arXiv:1712.093810, 2017.

[89] Timothy P. Lillicrap, Jonathan J. Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. In International Conference on Learning Representations, 2016.

[90] Minh-Thang Luong, Hieu Pham, and Christopher D. Manning. Effective approaches to attention-based neural machine translation. In Conference on Empirical Methods in Natural Language Processing, 2015.

[91] Corey Lynch and Pierre Sermanet. Language conditioned imitation learning over unstructured data. In Robotics: Science and Systems, 2021.

[92] Corey Lynch, Mohi Khansari, Ted Xiao, Vikash Kumar, Jonathan Tompson, Sergey Levine, and Pierre Sermanet. Learning latent plans from play. In Conference on Robot Learning, 2019.

[93] Tatsuya Matsushima, Hiroki Furuta, Yutaka Matsuo, Ofir Nachum, and Shixiang Shane Gu. Deployment-efficient reinforcement learning via model-based offline optimization. In International Conference on Learning Representations, 2021.

[94] Takeru Miyato, Toshiki Kataoka, Masanori Koyama, and Yuichi Yoshida. Spectral normalization for generative adversarial networks. In International Conference on Learning Representations, 2018.

[95] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. Nature, 2015.

[96] Volodymyr Mnih, Adrià Puigdomènech Badia, Mehdi Mirza, Alex Graves, Timothy P. Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. arXiv preprint arXiv:1602.01783, 2016.

[97] Shakir Mohamed and Danilo J Rezende. Variational information maximisation for intrinsically motivated reinforcement learning. In Advances in Neural Information Processing Systems, 2015.

[98] Susan A Murphy, Mark J van der Laan, James M Robins, and Conduct Problems Prevention Research Group. Marginal mean models for dynamic regimes. Journal of the American Statistical Association, 2001.

[99] Ofir Nachum, Shixiang Gu, Honglak Lee, and Sergey Levine. Data-Efficient Hierarchical Reinforcement Learning. In Advances in neural information processing systems, 2018.

[100] Ashvin Nair, Vitchyr Pong, Murtaza Dalal, Shikhar Bahl, Steven Lin, and Sergey Levine. Visual reinforcement learning with imagined goals. arXiv preprint arXiv:1807.04742, 2018.

[101] Andrew Y Ng and Stuart Russell. Algorithms for inverse reinforcement learning. In International Conference on Machine Learning, 2000.

[102] Manu Orsini, Anton Raichuk, Léonard Hussenot, Damien Vincent, Robert Dadashi, Sertan Girgin, Matthieu Geist, Olivier Bachem, Olivier Pietquin, and Marcin Andrychowicz. What matters for adversarial imitation learning? arXiv preprint arXiv:2106.00672, 2021.

[103] Pierre-Yves Oudeyer and Frederic Kaplan. What is intrinsic motivation? a typology of computational approaches. Frontiers in Neurorobotics, 2009.

[104] Deepak Pathak, Pulkit Agrawal, Alexei A. Efros, and Trevor Darrell. Curiosity-driven exploration by self-supervised prediction. In International Conference on Machine Learning, 2017.

[105] Vitchyr Pong, Shixiang Gu, Murtaza Dalal, and Sergey Levine. Temporal difference models: Model-free deep rl for model-based control. International Conference on Learning Representations, 2018.

[106] Vitchyr H Pong, Murtaza Dalal, Steven Lin, Ashvin Nair, Shikhar Bahl, and Sergey Levine. Skew-fit: State-covering self-supervised reinforcement learning. In International Conference on Machine Learning, 2020.

[107] Ben Poole, Sherjil Ozair, Aaron Van Den Oord, Alex Alemi, and George Tucker. On variational bounds of mutual information. In International Conference on Machine Learning, 2019.
[108] Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners, 2019.

[109] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. arXiv preprint arXiv:2103.00020, 2021.

[110] Antonin Raffin, Ashley Hill, Maximilian Enerstus, Adam Gleave, Anssi Kanervisto, and Noah Dormann. Stable baselines3, 2020. URL https://github.com/DLR-RM/stable-baselines3.

[111] Aditya Ramesh, Mikhail Pavlov, Gabriel Goh, Scott Gray, Chelsea Voss, Alec Radford, Mark Chen, and Ilya Sutskever. Zero-shot text-to-image generation. arXiv preprint arXiv:2102.12092, 2021.

[112] Balararan Ravindran and Andrew G Barto. Model minimization in hierarchical reinforcement learning. In Abstraction, Reformulation, and Approximation, 2002.

[113] Daniele Reda, Tianxin Tao, and Michiel van de Panne. Learning to locomote: Understanding how environment design matters for deep reinforcement learning. In Motion, Interaction and Games, 2020.

[114] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In Conference on Computer Vision and Pattern Recognition, 2016.

[115] Alfréd Rényi. On measures of entropy and information. In Berkeley Symposium on Mathematical Statistics and Probability, 1961.

[116] Danilo Jimenez Rezende and Shakir Mohamed. Variational inference with normalizing flows. In International Conference on Machine Learning, 2016.

[117] Andrei A. Rusu, Sergio Gomez Colmenarejo, Caglar Gulcehre, Guillaume Desjardins, James Kirkpatrick, Razvan Pascanu, Volodymyr Mnih, Koray Kavukcuoglu, and Raia Hadsell. Policy distillation. arXiv preprint arXiv:1511.06295, 2016.

[118] Andrei A. Rusu, Neil C. Rabinowitz, Guillaume Desjardins, Hubert Soyer, James Kirkpatrick, Koray Kavukcuoglu, Razvan Pascanu, and Raia Hadsell. Progressive neural networks. arXiv preprint arXiv:1606.04671, 2016.

[119] Christoph Salge, Cornelius Glackin, and Daniel Polani. Empowerment–An introduction. In Guided Self-Organization: Inception, pages 67–114. Springer, 2014.

[120] Tim Salimans, Jonathan Ho, Xi Chen, Szymon Sidor, and Ilya Sutskever. Evolution strategies as a scalable alternative to reinforcement learning. arXiv preprint arXiv:1703.03864, 2017.

[121] Manolis Savva, Abhishek Kadian, Oleksandr Maksymets, Yili Zhao, Erik Wijmans, Bhavana Jain, Julian Straub, Jia Liu, Vladlen Koltun, Jiendra Malik, Devi Parikh, and Dhruv Batra. Habitat: A platform for embodied ai research. In International Conference on Computer Vision, 2019.

[122] Tom Schaul, Dan Horgan, Karol Gregor, and David Silver. Universal Value Function Approximators. In International Conference on Machine Learning, 2015.

[123] Jrgen Schmidhuber. Formal theory of creativity, fun, and intrinsic motivation (1990-2010). IEEE transactions on autonomous mental development, 2010.

[124] John Schulman, Sergey Levine, Philipp Moritz, Michael Jordan, and Pieter Abbeel. Trust region policy optimization. In International Conference on Machine Learning, 2015.

[125] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. arXiv preprint arXiv:1707.06347, 2017.

[126] Archit Sharma, Michael Ahn, Sergey Levine, Vikash Kumar, Karol Hausman, and Shixiang Gu. Emergent real-world robotic skills via unsupervised off-policy reinforcement learning. In Robotics: Science and Systems, 2020.

[127] Archit Sharma, Shixiang Gu, Sergey Levine, Vikash Kumar, and Karol Hausman. Dynamics-aware unsupervised discovery of skills. In International conference on learning representations, 2020.

[128] Noah Y. Siegel, Jost Tobias Springenberg, Felix Berkenkamp, Abbas Abdolmaleki, Michael Neunert, Thomas Lampe, Roland Hafner, and Martin A. Riedmiller. Keep doing what worked: Behavioral modelling priors for offline reinforcement learning. In International Conference on Learning Representations, 2020.
[129] David Silver, Satinder Singh, Doina Precup, and Richard S Sutton. Reward is enough. *Artificial intelligence*, 2021.

[130] Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning: An Introduction*. The MIT Press, 2018.

[131] Yuval Tassa, Yotam Doron, Alistair Muldal, Tom Erez, Yazhe Li, Diego de Las Casas, David Budden, Abbas Abdolmaleki, Josh Merel, Andrew Lefrancq, Timothy Lillicrap, and Martin Riedmiller. Deepmind control suite. *arXiv preprint arXiv:1801.00690*, 2018.

[132] Open Ended Learning Team, Adam Stooke, Anuj Mahajan, Catarina Barros, Charlie Deck, Jakob Bauer, Jakub Sygnowski, Maja Trebac, Max Jaderberg, Michael Mathieu, Nat McAleese, Nathalie Bradley-Schmie, Nathaniel Wong, Nicolas Porcel, Roberta Raileanu, Steph Hughes-Fitt, Valentin Dalibard, and Wojciech Marian Czarnecki. Open-ended learning leads to generally capable agents. *arXiv preprint arXiv:2107.12808*, 2021.

[133] Emanuel Todorov, Tom Erez, and Yuval Tassa. Mujoco: A physics engine for model-based control. In *International Conference on Intelligent Robots and Systems*, 2012.

[134] Aaron van den Oord, Nal Kalchbrenner, and Koray Kavukcuoglu. Pixel recurrent neural networks. In *International Conference on Machine Learning*, 2016.

[135] Aaron van den Oord, Yazhe Li, and Oriol Vinyals. Representation learning with contrastive predictive coding. *arXiv preprint arXiv:1807.03748*, 2019.

[136] Francisco J. Varela, Eleanor Rosch, and Evan Thompson. *The Embodied Mind: Cognitive Science and Human Experience*. The MIT Press, 1991.

[137] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems*, 2017.

[138] Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. Show and tell: A neural image caption generator. In *International Conference on Computer Vision*, 2015.

[139] Oriol Vinyals, Timo Ewalds, Sergey Bartunov, Petko Georgiev, Alexander Sasha Vezhnevets, Michelle Yeo, Alireza Makhzani, Heinrich Küttler, John Agapiou, Julian Schrittwieser, John Quan, Stephen Gaffney, Stig Petersen, Karen Simonyan, Tom Schaul, Hado van Hasselt, David Silver, Timothy Lillicrap, Kevin Calderone, Paul Keet, Anthony Brunasso, David Lawrence, Anders Ekeromo, Jacob Repp, and Rodney Tsing. Starcraft ii: A new challenge for reinforcement learning. *arXiv preprint arXiv:1708.04782*, 2017.

[140] David Warde-Farley, Tom Van de Wiele, Tejas Kulkarni, Catalin Ionescu, Steven Hansen, and Volodymyr Mnih. Unsupervised Control Through Non-Parametric Discriminative Rewards. In *International Conference on Learning Representations*, 2019.

[141] Ronald J. Williams. Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Machine Learning*, 1992.

[142] Markus Wulfmeier, Peter Ondruska, and Ingmar Posner. Maximum entropy deep inverse reinforcement learning. *arXiv preprint arXiv:1507.04888*, 2015.

[143] Tianhe Yu, Deirdre Quillen, Zhanpeng He, Ryan Julian, Karol Hausman, Chelsea Finn, and Sergey Levine. Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning. In *Conference on Robot Learning*, 2019.

[144] Rui Zhao, Yang Gao, Pieter Abbeel, Volker Tresp, and Wei Xu. Mutual information state intrinsic control. In *International Conference on Learning Representations*, 2021.

[145] Brian D. Ziebart, Andrew L. Maas, J. Andrew Bagnell, and Anind K. Dey. Maximum entropy inverse reinforcement learning. In *AAAI conference on artificial intelligence*, 2008.
Appendix

A BRAXLINES Benchmark, Hyperparameters, Ablations, and Analyses

We detail the additional information for experimental results and BRAXLINES Benchmark. While BRAXLINES is designed more as a tool to enable rapid creation of environments and behaviors, it also provides minimal quantitative benchmarks that could be utilized as a reference for how to evaluate new environments or new MI-MAX and D-MIN algorithms. Such baselines for reward-free algorithms have been lacking, or non-existent, in open-source libraries (see Tables 5 and 6).

| Framework         | DDPG | A3C  | PPO  | TRPO | TD3  | SAC  | ES  |
|-------------------|------|------|------|------|------|------|-----|
| Baselines [29]    | ✓    | ✓    | ✓    | ✓    |      |      |     |
| Stable Baselines [110]| ✓    | ✓    |      |      | ✓    |      |     |
| RLLab [32]        |      |      | ✓    | ✓    |      | ✓    | ✓   |
| Tf-Agents [29]    | ✓    | ✓    | ✓    | ✓    | ✓    |      |     |
| RLLib [88]        | ✓    | ✓    | ✓    | ✓    | ✓    |      |     |
| PFRL [43]         | ✓    | ✓    | ✓    | ✓    | ✓    | ✓    | ✓   |
| BRAX/BRAXLINES(ours) |      |      | ✓    | ✓    | ✓    | ✓    | ✓   |

Table 5: A survey on the support of the most common continuous control, reward maximization algorithms from a set of well-maintained, stable RL baselines.

| Framework         | AIRL | GAIL | GCRL | DIAYN | cDIAYN | Oth. MI-MAX |
|-------------------|------|------|------|-------|--------|-------------|
| Baselines [29]    |      |      |      |       |        |             |
| Stable Baselines [110]|      |      |      |       |        |             |
| RLLab [32]        |      |      |      |       |        |             |
| Tf-Agents [29]    |      |      |      |       |        |             |
| RLLib [88]        |      |      |      |       |        |             |
| PFRL [43]         |      |      |      |       |        |             |
| BRAXLINES(ours)   | ✓    | ✓    | ✓    | ✓     | ✓      | ✓           |
| Kostrikov [76]    |      |      |      |       |        |             |
| Eysenbach et al. [34]|      |      | ✓    |       |        |             |
| Sharma et al. [127]|      |      |      | ✓     |        |             |
| Choi et al. [20]  |      |      |      |       |        |             |

Table 6: A survey on the support of the most common algorithms in MI-MAX and D-MIN families across a set of well-maintained, stable RL baselines. Since standard RL baselines rarely support advanced algorithms, we added a few additional codebases (some from original algorithmic papers). Note that Choi et al. [20] is empty since no code is open-sourced.

A.1 Hyperparameters

Hyperparameters for reproducing all the benchmark and experiment results can be found in https://github.com/google/brax/blob/main/brax/experimental/braxlines/experiments. These experiments can be easily run serially on Colab https://github.com/google/brax/blob/main/notebooks/braxlines/experiment_sweep.ipynb based on a configuration list of dictionaries such as https://github.com/google/brax/blob/main/brax/experimental/braxlines/experiments/mimax_sweep.py. Else, users can modify run_experiment() from https://github.com/google/brax/blob/main/brax/experimental/braxlines/experiments/__init__.py to launch parallel sweeps on their custom computing clusters.

Experiment Parameters We used 10 random seeds for each experiment result to compute its mean and variance. Similarly to [34, 127, 20], we assume prior knowledge on dimensions of interest, e.g. XY-velocities: obs_indices = (11,) for HalfCheetah, (13, 14) for Ant, and (22, 23) (see https://github.com/google/brax/blob/main/brax/experimental/composer/obs_descs.py), for learning (except DIAYN_FULL) and evaluation metrics.
Figure 5: MI-MAX results on Humanoid averaged over 10 seeds: (from left to right) (a) episodic discriminator reward, (b, c) MI(z,s) and H(s) estimates from Algorithm 1, and (d) LGR from Algorithm 3. Unlike Ant results in Figure 3, DIAYN performs the best both in terms of MI(z,s) and LGR metrics, better than GCRL. Since H(s) is the same for DIAYN and GCRL, this means that DIAYN acquired better on average controllability/consistency with respect to each given target goal (reasonable since DIAYN is only learning 8 targets, while GCRL is learning an infinite set of targets).

PPO Parameters We used the same exact hyperparameters for PPO as in task-reward RL examples in BRAX (see https://github.com/google/brax/blob/main/notebooks/training.ipynb for their original Colab and https://github.com/google/brax/tree/main/brax/experimental/braxlines/experiments/defaults.py for these PPO hyperparameters), except multiplying the num_timesteps by 2 to allow longer training than in the single-task setting. Fully-connected MLPs with linen.swish activation function and hidden sizes of [32, 32, 32, 32] are used for policy functions, and hidden sizes of [256, 256, 256, 256, 256] for value functions (see https://github.com/google/brax/blob/main/brax/training/networks.py).

MI-MAX Parameters The hyperparameters are specified in https://github.com/google/brax/blob/main/brax/experimental/braxlines/experiments/mimax_sweep.py. For discrete latent experiments (DIAYN and DIAYN_FULL), number of skills for z diayn_num_skills is set to 8. For continuous latent experiments (cDIAYN), the z dimension is set to 2. Fully-connected MLPs with linen.swish activation function and hidden sizes of [32, 32] are used for discriminator functions q(z|o(s)). See Section A.3 for ablations on key hyperparameters such as spectral_norm and diayn_num_skills.

D-MIN Parameters The hyperparameters are specified in https://github.com/google/brax/blob/main/brax/experimental/braxlines/experiments/dmin_sweep.py. Fully-connected MLPs with linen.swish activation function and hidden sizes of [32, 32] are used for binary discriminator functions. See Section A.3 for ablations on key hyperparameters such as gradient_penalty_weight.

COMPOSER Parameters BRAXLINES COMPOSER is designed as a toolkit for efficiently reusing environment components, observation definitions, and reward functions for composing new tasks or reward-free environments. Example “hyperparameters” of these environments are listed in https://github.com/google/brax/tree/main/brax/experimental/composer/env_descs.py. Similar to the rest of experiments, hyperparameter sweeps are supported. If the comparison is about the optimizability by PPO with respect to a task score, it is important to ensure that score_fns are the same across all swept variants. Examples include:

- **Sweeping Reward Function Parameters**: When you have a sum of multiple reward terms, it’s helpful to sweep over the scaling parameters to find the optimal trade-off among these to have the best task score of interest https://github.com/google/brax/blob/main/brax/experimental/braxlines/experiments/ant_push_sweep.py

- **Sweeping Morphology Parameters**: You could parameterize a component to have varying morphologies (e.g. different number of legs for Ant) https://github.com/google/brax/blob/main/brax/experimental/braxlines/experiments/ant_run_morphology_sweep.py

A.2 Additional Benchmark Results

MI-MAX Figure 5 and Figure 6 show learning curves and skill visualizations for Humanoid respectively. To the best of our knowledge, DADS [127] is one of the few unsupervised RL algorithms that scaled to Humanoid, and we are the first to report successful DIAYN results on it.

D-MIN Figure 7 shows learning curves and result visualization for Humanoid. Humanoid successfully learns to match the given bi-modal target distribution.
Figure 6: MI-MAX DIAYN skill visualization on Humanoid. Humanoid successfully learns to move in multiple directions. See behavior videos in https://github.com/google/brax/blob/main/brax/experimental/braxlines.

Figure 7: D-MIN results for Humanoid averaged over 10 seeds: (a, b) episode reward and energy distance metric across training iterations; (c, d) visualizations of learned policy state marginal distribution and the target. Unlike Ant results in Figure 4, AIRL and GAIL2 significantly outperforms GAIL. See behavior videos in https://github.com/google/brax/blob/main/brax/experimental/braxlines.

**BRAXLINES COMPOSER**  Figure 8 show training results for environment examples in Figure 2. For Ant Push, we observe that “scale” which balances between object-to-target-velocity and ant-to-object reward terms has significant effect on final scores (since “episode_reward” is a variable here, we defined “episode_score” as a consistent metric for evaluation). For the morphologically-varying Ant Run, we observe that the running performance is largely consistent, with an exception in the case of two legs. Importantly, as described by simple examples in Appendix A.1 and D, COMPOSER allows simple programming of environment variations and hyperparameter sweeps.

### A.3 Ablation Studies and Analysis

This section mainly lists a few design parameters that are critical to getting interesting emergent behaviors. For more examples, check out our codebase or directly try out our interactive Google Colabs in https://github.com/google/brax/tree/main/notebooks/braxlines.

**Spectral Normalization**  MI-MAX algorithms exhibit complex learning dynamics through continuously changing reward functions. Choi et al. [20] showed that the use of spectral normalization (SN) can significantly stabilize learning and quality of discovered skills. Figure 9 and Figure 10 show that SN does improve DIAYN results substantially in MI(z,s)and H(s), in both Ant and Humanoid. We also show in Figure 11 that even cDIAYN can discover meaningful skills, which has been difficult in prior works [34, 127, 20]. This result, along with our success with Humanoid, is likely because most prior results built on SAC which is more sample-efficient but less stable than PPO.

**Gradient Penalty**  D-MIN algorithms also exhibit difficult learning dynamics, and many prior works utilized numerous additional implementations to stabilize learning, such as separately learning terminal reward for bias correction [77, 102] and fictitious play [83]. Contrary to prior wisdom, Figure 12 shows that gradient penalty does not significantly improve the learning performances for these bi-modal target matching tasks in Ant or Humanoid.

**Feature Engineering o(s)**  Figure 13 shows qualitative results of MI-MAX with or without feature engineering o(s) (DIAYN or DIAYN_FULL). As different dimensions have different sensitivity to the agent’s actions, often the easiest dimension is diversified first to maximize the objective in discriminative MI-MAX, i.e. in DIAYN_FULL Ant just learns to make slightly different poses. By removing uninteresting and trivial dimen-
Figure 8: Task parameter sweeps on (left and middle) Ant Push and (right) morphological Ant Run in Figure 2. See behavior videos in https://github.com/google/brax/blob/main/brax/experimental/braxlines.

Figure 9: MI-MAX results on Ant with and without Spectral Normalization (“sn_F” means no spectral norm) averaged over 10 seeds: (from left to right) (a) episodic discriminator reward, (b, c) MI(z,s) and H(s) estimates from Algorithm 1, and (d) LGR from Algorithm 3.

sions for control, the agent can effectively focus on controlling the key dimensions such as XY velocities (dim = (13, 14)). Our fast interactive tool allows efficiently iterating different feature choices.

Additionally, Figure 14 and Figure 15 provide a deeper look into MI and H(s) estimates across first 30 dimensions Ant, DIAYN or DIAYN_FULL. This essentially evaluates intrinsic controllability that the agent has over the environment, from which we can gain quantitative intuitions about the agent’s behaviors as well as its affinity with the environment. For example, DIAYN learns to run in different directions (dim=(13,14)), but as it runs it does not change its Z-axis orientation (dim=1) and therefore indirectly gained controllability over it. If we can measure such indirect relationships among dimensions, we can more efficiently design minimal features o(s). Furthermore, combining with the insights from policy information capacity (PIC) [45], we can choose to design environments or random initial policies such that the initial MI is already high with respect to the dimensions of interest, i.e. designing environments and agents for optimizability [45, 113].

**Task-Reward Reward Augmentation** When a task reward is combined with MI-MAX (env_reward_multiplier > 0), it essentially diversifies policies while accomplishing a given task, i.e. learning multiple independent ways of accomplishing the task. Such auxiliary task reward can sometimes be as simple as a positive survival reward (which is used in all our MI-MAX and D-MIN experiments as listed in Table 2), if the environment itself is non-trivial and has termination like the Humanoid environment [127]. In Figure 13, the standard Ant’s forward running reward is combined, and it learns different gait behaviors.
Figure 10: MI-MAX results on Humanoid with and without Spectral Normalization ("sn_F" means no spectral norm) averaged over 10 seeds: (from left to right) (a) episodic discriminator reward, (b, c) MI(z,s) and H(s) estimates from Algorithm 1, and (d) LGR from Algorithm 3.

Figure 11: Skills visualization for (from left to right) (a) DIAYN without spectral normalization (SN), (b) DIAYN with SN, (c) continuous DIAYN (cDIAYN) without SN, and (d) cDIAYN with SN. DIAYN with continuous z has been notoriously difficult even with feature engineering, where Eysenbach et al. [34] and Sharma et al. [127] have not showed successful skill learning. A simple combination of PPO [125] and spectral normalization (SN) [94] has proven to be surprisingly effective and enabled training a continuous-latent DIAYN (while results are slightly worse than those of discrete-latent DIAYN according to Figure 3).

Figure 12: D-MIN results for Ant with or without Gradient Penalty ("gpw" stands for gradient penalty weight) averaged over 10 seeds: (from left to right) (a, b) episode reward and energy distance metric across training iterations for AIRL; (c, d) episode reward and energy distance metric across training iterations for GAIL. Both BRAXLINES AIRL and GAIL are stable with or without gradient penalties, and too much penalty can degrade performances.
Figure 13: The importance of feature engineering (o(s)) and reward augmentation (env_reward_multiplier) to discover diverse behaviors when running (a) DIAYN [34] with full observation (DIAYN_FULL), (b) DIAYN with XY-velocities (dim=(13,14)), (c) DIAYN with XY + adding original reward on Brax’s Ant [37]. Naively using full states does not lead to interesting behaviors like walking or hopping (it just learns to pose differently). With simple specification of dimensions in observation, however, its learns very effectively. Simple feature engineering and MI-MAX is therefore a powerful tool for behavior engineering without much human efforts. Additionally, if there is some task reward available, it can be added to automatically discover multiple distinguishable ways of accomplishing the same task.

Figure 14: Mutual information evaluations across first 30 dimensions on Ant. We analyzed two configurations: DIAYN uses o(s[13, 14]) (i.e., the XY velocities of the root), while DIAYN_FULL uses the full state. The red background indicates when DIAYN is higher than DIAYN_FULL more than 80% of the time and blue if vice versa. While it is unsurprising that DIAYN excels at gaining controllability over specified dimensions (13, 14), it is interesting that DIAYN additionally gained controllability over dim=1 (i.e., the first rotation angle of the root) and lost controllability over dim=(0, 2) (the height and other rotation angles of the root) as an indirect consequence of empowering dim=(13,14).
Figure 15: Entropy evaluations across first 30 dimensions on Ant. DIAYN uses $o(s_{[13, 14]})$ (corresponding to $xy$ velocities), while DIAYN_FULL uses identity $o$ (full observation state). It is noticeably to note that in all dimensions DIAYN (XY) gains higher state entropies than DIAYN (full state). Contrasting this result with Figure 14, we can conclude that while DIAYN (XY) can thoroughly increase marginal entropies, it can only gain controllabilities (low conditional entropies) over a limited set of the dimensions. In cases where you only care about marginal entropies such as for risk-seeking exploration, this may be desired over controllability.
B Latent Goal Reaching

Algorithm 3 estimates the LGR metric [20] of a policy $\pi(a|s, z)$. This has exact correspondence with the standard goal-reaching objective in GCRL.

**Algorithm 3: Latent Goal Reaching** [20]

**Input:** agent $\pi(a|s, z); o(s)$; goals $\alpha^*_{i,L} = o(s^*_{i,L}) \sim p^*(s)$; inference $q(z|o(s))$

**Output:** LGR estimate $\hat{LGR}$

1. Sample $z_{l,n} \sim q(z|s^*_l)$ // Infer $N$ latent intents per goal $s^*_l$
2. Sample $s_{l,n,m,t} \sim \pi(\cdot|\cdot,z_{l,n})$ in $\mu$ // Collect $M$ episodes of horizon $T$ per $z_{l,n}$
3. Infer $LGR = \sum_{l,n,m,t} \frac{-(\alpha^*_l - o(s_{l,n,m,t}))^2}{\sigma^2}$

B.1 Justification for Negative Latent Goal Reaching as an Empowerment Approximation

Given $p^*(z) = \arg \max_{p(z)} I_\pi(z, o(S^\mu))$, the empowerment per environment $\mu$ is given by:

$$p^*(z)p(o(S^\mu)|z) = p^*(o(S^\mu))p^*(z|o(S^\mu))$$

$$I^*_\pi(z, o(S^\mu)) = H^*(o(S^\mu)) - H^*(o(S^\mu)|z)$$

where $C_1 = H^*(o(S^\mu))$ is now just a constant offset due to our assumption (1) that does not depend on the evaluation agent $\pi$. Eq. (10) is equivalently the variational autoencoder objective [73], except in RL we need to somehow estimate $\log p(o(S^\mu)|z)$. One way is to fit a density estimation model [83, 11], but to make a direct connection to goal-reaching performances, we instead use a non-parametric density estimation based on a mixture of Gaussians. Following the notations in Algorithm 3,

$$\log p(o^*_i|z_{l,n}) \approx \log \frac{1}{MT} \sum_{m,t} N(o^*_i|o_{l,n,m,t}, \sigma^2 I)$$

$$\geq \sum_{m,t} -(\alpha^*_i - o_{l,n,m,t})^2 / \sigma^2 + C_2,$$

where Eq. 12 follows from a simple application of Jensen’s inequality, and $C_2$ is again a constant offset that does not depend on $\pi$. 

25
C Prior Evaluation Methodologies for MI-MAX and D-MIN Algorithms

In this section, we briefly summarize prior evaluation methodologies for MI-MAX and D-MIN families, and relation to the metrics in the BRAXLINES. Since the inferred reward function dynamically changes during training, could have an arbitrary range of values, and largely depends on the different implementation and hyperparameter choices such as \( z \)-space in MI-MAX, or reward transformation in D-MIN, it is difficult to apply episodic reward for quantitatively evaluating convergence or final performances. As in Table 7, most of evaluations for MI-MAX and D-MIN have relied on qualitative comparisons, visualization of rollout videos or density plots [34, 127, 46, 83], or down-stream task performances [34, 127, 126]. Qualitative evaluation might be hard to ensure objectiveness and automate the whole process, and the evaluation with down-stream tasks may not correspond with the quality of generated behaviors themselves. While previous D-MIN algorithms mostly focus on imitation learning and frequently use task rewards directly to compare how close to the experts they got [63, 38, 46], such evaluation is not suitable for the distribution sketching case in our paper.

Recently, Kim et al. [72] employ SEPIN@\( k \) and W SEPIN, which are proposed in the disentangled representation learning literature [30], for the quantitative evaluation of MI-MAX algorithms. Both SEPIN@\( k \) and W SEPIN consider the mutual information between the skills \( Z \) and the last states of the trajectories with specified dimensions \( o(S_T) \). SEPIN@\( k \) is the top-\( k \) average of \( \text{MI}(o(S_T), Z_i; Z_{\rho_i}) \) over skills \( i = 1, 2, \ldots \), and W SEPIN is the weighted sum of \( \text{MI}(o(S_T), Z_i; Z_{\rho_i}) \) over skills. They also propose to simply use \( \text{MI}(o(S_T), Z) \) as an information theoretic metrics. See Kim et al. [72] for the detailed discussion. Because they consider the last states the agents reached and measure how they are different depending on \( z \), these might be similar metrics to LGR.

| Family  | Metrics                        | Type            | Hyperparameter-Agnostic | References          |
|---------|--------------------------------|-----------------|-------------------------|---------------------|
| MI-MAX  | Episodic Discriminator Reward  | Quantitative    | No                      | –                   |
| MI-MAX  | Diversity in Rollout Videos   | Qualitative     | Yes                     | [34, 127, 36, 72]   |
| MI-MAX  | Downstream Task Performance    | Quantitative    | Yes                     | [34, 127, 36, 56, 50]|
| MI-MAX  | SEPIN@\( k \), W SEPIN [30]   | Quantitative    | Yes                     | [72]                |
| D-MIN   | Episodic Inferred Reward       | Quantitative    | No                      | –                   |
| D-MIN   | Density Visualization          | Qualitative     | Yes                     | [46, 83]            |
| D-MIN   | Imitation Task Performance     | Quantitative    | Yes                     | [63, 38, 46]        |
| MI-MAX  | Particle-based MI Estimation   | Quantitative    | Yes                     | Ours, [45]          |
| MI-MAX  | Latent Goal Reaching           | Quantitative    | Yes                     | Ours, [20]          |
| D-MIN   | Energy Distance                | Quantitative    | Yes                     | Ours                |

Table 7: A summary of prior evaluation methods for MI-MAX and D-MIN algorithms.
D BRAXLINES COMPOSER API Example

We made possible in BRAXLINES COMPOSER to design continuous control tasks with under 50 lines of code (including comments). The code snippet below shows how to construct a manipulation, goal-conditioned task that we coined ant-push. We made available several off-the-shelf components\(^4\) for rapid prototyping. These components were designed with flexibility in mind, making them amenable for procedurally-generated continuous control tasks or for learning modular policies\(^{64, 81}\) that can control multiple morphologies.

For a complete running example and a more in-depth introduction to BRAXLINES COMPOSER, check out the Composer Basics\(^5\) notebook.

```python
from brax.experimental.composer import composer

env_desc = dict(
    components=dict(  # component information
        agent1=dict(  # pro_ant is a provided off-the-shelf component
            component='pro_ant',  # defined at components/pro_ant.py
            component_params=dict(num_legs=6)  # ant with 6 legs
        ),
        cap1=dict(  # the singleton is the ball the ant controls
            component='singleton',  # defined in components/singleton.py
            component_params=dict(size=0.5),  # a ball with radius 0.5
            pos=(1, 0, 0),  # where to place a capsule object
            reward_fns=dict(  # reward1: a GCRL task
                goal=dict(  # root_goal is the target vector
                    reward_type='vel',
                    target_goal=(4, 0, 0)  # a target velocity for the object
                )
            )
        ),
        edges=dict(  # edge information
            agent1__cap1=dict(  # edge names use sorted component names
                extra_observers=[  # add agent-object position diff as an extra obs
                    dict(observer_type='root_vec')
                ],
                reward_fns=dict(  # reward2: make the agent close to the object
                    dist=dict(reward_type='root_dist')
                )
            )
        )
    ),
    env = composer.create(env_desc=env_desc)  # Composer returns a functional environment
```

\(^4\)Available at https://github.com/google/brax/tree/main/brax/experimental/composer/components

\(^5\)Available at https://colab.research.google.com/github/google/brax/blob/main/notebooks/composer/composer.ipynb