
PWM: Policy Learning with Large World Models

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Abstract

1 Reinforcement Learning (RL) has achieved impressive results on complex tasks
2 but struggles in multi-task settings with different embodiments. World models
3 offer scalability by learning a simulation of the environment, yet they often rely
4 on inefficient gradient-free optimization methods. We introduce Policy learn-
5 ing with large World Models (PWM), a novel model-based RL algorithm that
6 learns continuous control policies from large multi-task world models. By pre-
7 training the world model on offline data and using it for first-order gradient policy
8 learning, PWM effectively solves tasks with up to 152 action dimensions and
9 outperforms methods using ground-truth dynamics. Additionally, PWM scales
10 to an 80-task setting, achieving up to 27% higher rewards than existing baselines
11 without the need for expensive online planning. Visualizations and code available
12 at policy-world-model.github.io

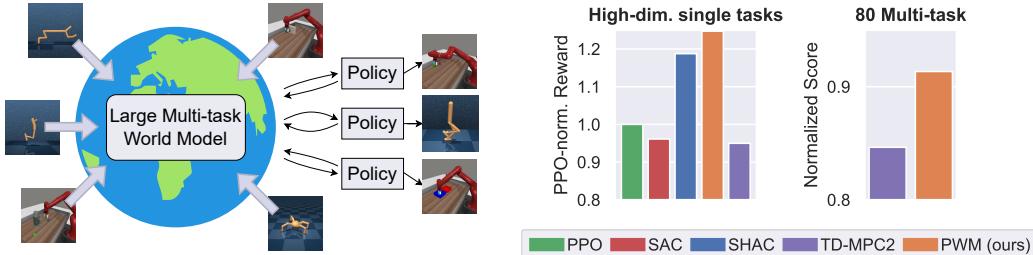


Figure 1: We propose PWM, a novel approach to scalable RL where we harness large multi-task world models to rapidly train model-based RL policies using efficient first-order gradients. When the world models used are regularized and avoid exploding gradients, this results in efficient policy learning in ≤ 10 minutes per task, while achieving higher reward in both single-task and multi-task settings.

13 1 Introduction

14 The pursuit of generalizability in machine learning has recently been propelled by the training of
15 large models on substantial datasets [7, 22, 4]. Such advancements have notably permeated robotics,
16 where multi-task behavior cloning techniques have shown remarkable performance [48, 32, 12, 5].
17 Nevertheless, these approaches predominantly hinge on near-expert data and struggle with adaptability
18 across diverse robot morphologies due to their dependence on teleoperation [48, 32, 24].

19 In contrast, Reinforcement Learning (RL) offers a robust framework capable of learning from
20 suboptimal data, addressing the aforementioned limitations. However, traditional RL has been
21 focused on single-task experts [29, 39, 13]. Recent work suggests that a potential pathway to multi-
22 task RL is with the world models framework, where a large-scale pre-trained model learns the

23 environment dynamics and is then combined with zeroth-order online planning to solve various tasks
24 [8, 36, 45, 9, 16, 37].

25 Despite advancements, zeroth-order methods often result in suboptimal solutions due to high variance
26 [30, 40, 34] and online planning time scales with model size, rendering them infeasible at scale
27 [37, 16]. These issues are particularly noticeable in world models with billions of parameters such
28 as GAIA-1 [19] and UniSim [46]. To address these challenges, we suggest a new approach: using
29 world models as scalable, differentiable physics simulators to enable efficient policy learning through
30 First-order Gradients (FoG). They have demonstrated better performance and stability than traditional
31 zeroth-order methods [44, 11]. FoGs have been previously paired with world models approaches
32 [14, 15] but often as complete algorithms that do not study the optimization landscape induced by the
33 world models. [26] studied these landscapes but focused on different learning architectures and did
34 not scale their results. In this work, we analyze world models with differentiable simulation principles
35 and find that the utility of world models lies not in their sheer accuracy but in (1) their smoothness,
36 (2) their optimality gap, and (3) their gradient stability over long-horizon forecasts [40, 18].

37 Building on these insights, we introduce Policy learning with large World Models (PWM), a novel
38 Model-Based RL (MBRL) algorithm and framework aimed at deriving effective continuous control
39 policies from large, multi-task world models. We utilize pre-trained TD-MPC2 world models
40 to efficiently learn control policies with FoG in <10m per task. Our empirical evaluations on
41 complex locomotion tasks indicate that PWM not only achieves higher reward than baselines but also
42 outperforms methods that use ground-truth simulation dynamics. In a multi-task scenario utilizing a
43 pre-trained 48M parameter world model, PWM achieves up to 27% higher reward than TD-MPC2
44 without relying on online planning.

45 This underscores the efficacy of PWM and supports our broader contributions:

- 46 1. Through pedagogical examples and ablations, we show that more accurate world models do
47 not translate to better performing policies. Instead of pursuing world model improvements
48 in isolation, we should aim to build world models that result in better policies.
- 49 2. When regularized correctly, world models enable efficient first-order optimization. We show
50 that this results in better performing policies and faster training times in comparison to
51 zeroth-order gradient methods.
- 52 3. We propose PWM, an algorithm for learning expert policies from large multi-task world
53 models in minutes using First-order Gradients (FoG).

54 2 Related work

55 RL approaches can be classified as model-based and model-free which assume and do not assume a
56 model respectively [2]. Most common algorithms for real-world applications such as PPO [39] and
57 SAC [13] are model-free and fall in the category of on-policy and off-policy methods respectively [2].
58 Both harness an actor-critic architecture where the critic learns the value and the actor optimizes the
59 critic directly to maximize cumulative rewards [23]. Off-policy methods such as SAC typically learn
60 a policy by taking First-order Gradients (FoG) directly from the critic. FoGs optimization typically
61 has lower variance but is affected by discontinuities of the objective [30]. On-policy methods such
62 as PPO harness zeroth-order gradients to learn policies [42]. These gradients are not affected by
63 discontinuities, making them effective for robotic tasks such as locomotion [35] but also exhibit
64 high variance, which leads to slow optimization and suboptimal solutions [30, 40]. Differentiable
65 simulation has been a popular framework to explore the properties of these gradient types [40, 18, 44].

66 While RL remains mostly focused on single-task policies, the larger robotics community has shifted
67 focus to large multi-task models relying on behavior cloning [10]. RT-1 [6] trains a large Transformer
68 sequence model on a vast dataset to perform low-level object manipulation on a real robot. RT-2
69 [48] extends this by pre-training an even larger model on internet-scale data to also do planning and
70 grasp affordance. Most recently, Open X [33] and Octo [32] showed that training these approaches
71 on different tasks and embodiment leads to increased performance on single-task single-embodiment
72 evaluations. Unfortunately, the benefits of large models and large datasets have not been sufficiently
73 explored in the context of RL. DreamerV3 [15] is a Model-Based Reinforcement Learning (MBRL)
74 approach which learns a representation of its environment with encoder, decoder, dynamics and
75 reward modules (collectively dubbed *world model*). It showed that scaling to larger models (400M

76 parameters) leads to higher data efficient and episode rewards. TD-MPC2 [16] continued this trend
 77 by employing a 317M parameter world model to learn an online planning multi-task policy capable of
 78 achieving good performance on 80 tasks. While showing impressive multi-task scalability, TD-MPC2
 79 fails to solve all tasks it was trained on and exhibits limited scalability due to its use of online planning.
 80 With world models increasingly growing in size, we need a policy learning technique capable of
 81 scaling to billion parameter world models such as GAIA-1 [19] or UniSim [46].

82 3 Background

83 We focus on discrete-time and infinite horizon Reinforcement Learning (RL) scenarios characterized
 84 by system states $s \in \mathbb{R}^n = \mathcal{S}$, actions $a \in \mathbb{R}^m = \mathcal{A}$, dynamics function $f : \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}$ and a reward
 85 function $r : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$. Combined, these form a Markov Decision Problem (MDP) summarized by
 86 the tuple $(\mathcal{S}, \mathcal{A}, f, r, \gamma)$ where γ is the discount factor. Actions at each timestep t are sampled from
 87 a stochastic policy $a_t \sim \pi_\theta(\cdot | s_t)$, parameterized by θ . The goal of the policy is to maximize the
 88 cumulative discounted rewards:

$$\max_{\theta} J(\theta) := \max_{\theta} \mathbb{E}_{\substack{s_1 \sim \rho(\cdot) \\ a_t \sim \pi_\theta(\cdot | s_t)}} \left[\sum_{t=1}^{\infty} \gamma^t r(s_t, a_t) \right] \quad (1)$$

89 where $\rho(s_1)$ is the initial state distribution. Since this maximization over an infinite sum is intractable,
 90 in practice we often maximize over a value estimate. The value of a state s_t is defined as the expected
 91 reward follow the policy π_θ

$$V_\psi^\pi(s_t) := \mathbb{E}_{a_h \sim \pi_\theta(\cdot | s_h)} \left[\sum_{h=t}^{\infty} \gamma^h r(s_h, a_h) \right] \quad (2)$$

92 When V is approximated with a learned model with parameters ψ and π_θ attempts to maximize some
 93 function of V , we arrive at the popular and successful actor-critic architecture [23]. Additionally,
 94 in MBRL it is common to also learn approximations of f and r , which we denote as F_ϕ and R_ϕ ,
 95 respectively. It has also been shown to be beneficial to encode the true state s into a latent state z
 96 using a learned encoder E_ϕ [14, 17, 16, 15]. Putting together all of these components we can define
 97 a model-based actor-critic algorithm to consist of the tuple $(\pi_\theta, V_\psi, E_\phi, F_\phi, R_\phi)$ which can describe
 98 popular approaches such as Dreamer [14] and TD-MPC2 [16]. Notably, we make an important
 99 distinction between the types of components. We refer to E_ϕ , F_ϕ and R_ϕ as the *world model*
 100 components since they are a supervised learning problem with fixed targets. On the other hand, π_θ
 101 and V_ψ optimize for moving targets which is fundamentally more challenging and we refer to them
 102 as the *policy components*.

103 4 Policy optimization through learned world models

104 This paper builds on the insight that since access to F_ϕ and R_ϕ is assumed through a pre-trained
 105 world-model, we have the option to optimize Eq. 1 via *First-order Gradient (FoG) optimization*
 106 which exhibit lower gradient variance, more optimal solutions and improved sample efficiency [30].
 107 In our setting, these types of gradients are obtained by directly differentiating the expected terms of
 108 Eq. 1 as shown in Eq. 3. Note that this gradient estimator is also known as reparameterized gradient
 109 [21] and pathwise derivative [38]. While we use the explicit $\nabla^{[1]}$ notation below, we later drop it for
 110 simplicity as all gradient types in this work are first-order gradients.

$$\nabla_{\theta}^{[1]} J(\theta) := \mathbb{E}_{\substack{s_1 \sim \rho(\cdot) \\ a_h \sim \pi_\theta(\cdot | s_h)}} \left[\nabla_{\theta} \left(\sum_{t=1}^{\infty} \gamma^t r(s_t, a_t) \right) \right] \quad (3)$$

111 As $\nabla_{\theta}^{[1]} J(\theta)$ in itself is a random variable, we need to estimate it. A popular way to do that in practice
 112 is via Monte-Carlo approximation where we are interested in two properties - bias and variance. In
 113 Sections 4.1 and 4.2 we tackle each aspect with toy robotic control problem to build intuition. In
 114 Section 4.3 we combine our findings to propose a new algorithm.

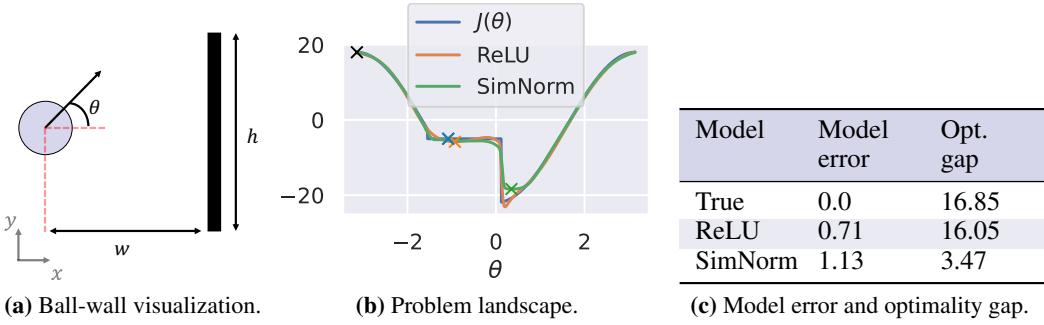


Figure 2: Ball-wall pedagogical example. The left figure visualizes the problem. The middle figure shows the problem landscape induced by each model. $J(\theta)$ shows the true underlying function and the two other are MLPs with different activation functions. We minimize each of these problems using gradient descent and starting at $\theta = -\pi$ (marker \times). The colored crosses represent the solutions converged to for each model. The right table shows the model approximation error during training and the optimality gap $|J(\theta^*) - J(\hat{\theta})|$ between the global minimum θ^* and the solution found for each model $\hat{\theta}$.

115 4.1 Learning through contact

116 FoGs are unbiased $\mathbb{E}[\bar{\nabla}^{[1]} J(\theta)] := \mathbb{E}\left[\sum_{n=1}^N \hat{\nabla}_n^{[1]} J(\theta)\right] = \nabla J(\theta)$, only if both the dynamics f
 117 and rewards r are Lipschitz-smooth [40]. However, many robotic problems involving contact are
 118 inherently non-smooth, which breaks these conditions and results in gradient sample error where
 119 $\mathbb{E}[\bar{\nabla}^{[1]} J(\theta)] \neq \nabla J(\theta)$ under finite number of samples N . Instead of directly optimizing the true,
 120 discontinuous objective, it is advantageous to optimize a smooth surrogate, such as a model learned
 121 by a regularized deep neural network.

122 To illustrate this concept, we use a toy problem where a ball is thrown toward a wall at a fixed velocity
 123 as shown in Figure 2a. The objective is to find the optimal initial angle θ such that we maximize
 124 forward distance. In this simplified pedagogical example, we assume that the ball "sticks" to the
 125 wall, creating a discontinuous optimization landscape (Figure 2b). We compare the performance of
 126 two models in approximating this objective: a 2-layer Multi-Layer Perceptron (MLP) with ReLU
 127 activation and another MLP with SimNorm activation [16] in the intermediate layers. SimNorm
 128 normalizes a latent vector z by projecting it into simplices with dimension V using a softmax operator.
 129 Given an input vector z , SimNorm can be expressed as a mapping into L vectors:

$$\text{SimNorm}(z) := [g_1, \dots, g_L], \quad g_i = \text{Softmax}(z_{i:i+V}) \quad (4)$$

130 We train the MLPs and observe the smoothing effects of the learned models in Figure 2b. While
 131 the MLP smooths the problem landscape, it also introduces a local minimum when attempting
 132 to optimize with gradient descent starting from (e.g.) $\theta = -\pi$, leading to a large optimality gap
 133 (difference between the solution and the optimal solution: $\|\hat{\theta} - \theta^*\|$). In contrast, the SimNorm MLP
 134 has additional regularization which reduces the optimality gap, at the expense of model accuracy
 135 (Table 2c). Therefore, we believe that regularized learned models can reduce gradient sample error,
 136 and thus the optimality gap, enabling more efficient FoG optimization in non-smooth environments.
 137 Further details in Appendix A.

138 4.2 Learning with chaotic dynamics

139 While first-order gradient estimators (FoGs) have lower variance per step, they can accumulate
 140 significant variance over long-horizon rollouts [27]. [40] link this variance to the smoothness of
 141 models and the length of the prediction horizon: $\text{Var}[\nabla J^{[1]}] \propto \|\nabla f(s, a)\|^{2H}$. At sufficiently high
 142 H , the high variance renders FoGs ineffective in chaotic systems. Chaotic systems are characterized
 143 by their sensitivity to initial conditions, where small perturbations can lead to exponentially divergent
 144 trajectories, making long-term prediction particularly challenging. The double pendulum, also known
 145 as the Acrobot [31], is a classic example of such a system (Figure 3).

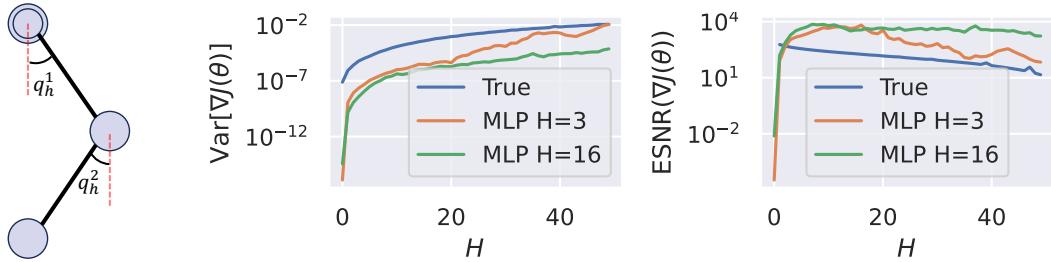


Figure 3: Double pendulum pedagogical example. The middle figure evaluates the variance of policy gradient estimates over $N = 100$ Monte-Carlo samples for varying horizons H . The right figure shows the same data but plots the Expected Signal-to-Noise ratio (ESNR) with higher values translating to more useful gradients. These results suggest that world models trained over long horizon trajectories provide more useful gradients. Note that $H = 3$ and $H = 16$ in the figure legends refer to the training horizon of the models.

146 We analyze the variance of gradient estimators in the double pendulum using both the true dynamics
 147 and a SimNorm-activated MLP model. The MLP model was trained for auto-regressive prediction
 148 horizons of $H = 3$ and $H = 16$ until convergence on a large dataset. Figure 3 shows that both
 149 learned models exhibit reduced variance compared to the true dynamics. However, as noted by [34],
 150 variance alone is insufficient for drawing definitive conclusions about gradient quality. Instead, they
 151 propose analyzing gradients via their Expected Signal-to-Noise Ratio (ESNR), defined as:

$$\text{ESNR}(\nabla J(\theta)) = \mathbb{E} \left[\frac{\sum \mathbb{E} [\nabla^{[1]} J(\theta)]^2}{\sum \text{Var} [\nabla^{[1]} J(\theta)]} \right] \quad (5)$$

152 In Figure 3, we observe that learned models exhibit higher ESNR than the true dynamics, providing
 153 more useful gradients. Notably, the training horizon plays a critical role, with the $H = 16$ model
 154 sustaining a higher ESNR over higher H . We conclude that learned world models offer more
 155 informative policy gradients than the true system dynamics. Further details in Appendix B.

156 4.3 PWM: an efficient policy learning method

157 Given the results from the previous
 158 subsection, we propose to view world
 159 models not as components of RL
 160 methods but instead as scalable dif-
 161 ferentiable physics simulators which
 162 provide gradients with low sample er-
 163 ror and variance. It is worth noting
 164 that approaches such as TD-MPC2
 165 [16] do not exploit these properties
 166 but rather choose to optimize policies
 167 via DDPG-style gradients:

$$\nabla_{\theta} J(\theta) \approx \mathbb{E}_{a \sim \pi(\cdot|s)} [\nabla_{\theta} Q(s, a)].$$

168 We propose a new method and frame-
 169 work for learning policies from large
 170 multi-task world models.

171 **Framework.** Assuming availability
 172 of data from multiple tasks, we first
 173 train a multi-task world model to pre-
 174 dict future states and rewards. Then
 175 for each task we want to solve, we
 176 learn a single policy in minutes us-
 177 ing FoG optimization. The policy is
 178 then deployed to solve the task and op-
 179 tionally finetune its world model and
 180 policy. We dub this PWM: Policy op-
 181 timization through World Models.

Algorithm 1: PWM: Policy Learning with large World Models

Given: Multi-task dataset \mathcal{B}
Given: γ : discount rate
Given: $\alpha_{\theta}, \alpha_{\psi}, \alpha_{\phi}$: learning rates
Initialize learnable parameters θ, ψ, ϕ
 ▷ Pre-train world model once
for N epochs **do**

$$s_{1:H}, a_{1:H}, r_{1:H}, e \sim \mathcal{B}$$

$$\phi \leftarrow \phi + \alpha_{\phi} \mathcal{L}_{wm}(\phi) \quad \triangleright \text{Eq. } 10$$
end
 ▷ Train policy on task embedding e
for M epochs **do**

$$s_1 \sim \mathcal{B}$$

$$z_1 = E_{\phi}(s_1, e)$$
for $h=[1, \dots, H]$ **do** ▷ Rollout

$$a_h \sim \pi_{\theta}(\cdot | z_h)$$

$$r_h = R_{\phi}(z_h, a_h, e)$$

$$z_{h+1} = F_{\phi}(z_h, a_h, e)$$
end

$$\theta \leftarrow \theta + \alpha_{\theta} \mathcal{L}_{\pi}(\theta) \quad \triangleright \text{Eq. } 7-9$$

$$\psi \leftarrow \psi + \alpha_{\psi} \mathcal{L}_V(\psi) \quad \triangleright \text{Eq. } 6$$
end

183 **Method.** For policy learning, we propose on-policy actor-critic approach where the actor is trained
 184 via FoG back-propagated through the world model, while the critic is trained via $\text{TD}(\lambda)$. The key to
 185 our approach is that training is done in a batched fashion where multiple trajectories are imagined in
 186 parallel. The actor loss function is akin to 1 but features rewards over a fixed horizon H , terminal
 187 value bootstrapping and usage of the learned world model components:

$$\mathcal{L}_\pi(\boldsymbol{\theta}) := \mathbb{E}_{\substack{\mathbf{s}_1 \sim \rho(\cdot) \\ \mathbf{a}_h \sim \pi_\theta(\cdot | \mathbf{z}_h)}} \left[\sum_{h=1}^{H-1} \gamma^h R_\phi(\mathbf{z}_h, \mathbf{a}_h) + \gamma^H V_\psi(\mathbf{z}_H) \right] \quad \text{where} \quad \begin{aligned} \mathbf{z}_1 &= E_\phi(\mathbf{s}_1) \\ \mathbf{z}_{t+1} &= F_\phi(\mathbf{z}_t, \mathbf{a}_t) \end{aligned} \quad (6)$$

188 The critic is trained in a model-free fashion using $\text{TD}(\lambda)$ over an H -step rollout in latent space \mathbf{z} as
 189 seen in other similar on-policy methods [41, 14, 44]:

$$V_h(\mathbf{z}_t) := \sum_{n=t}^{t+h-1} \gamma^{n-t} R_\phi(\mathbf{z}_n, \mathbf{a}_n) + \gamma^{t+h} V_\psi(\mathbf{z}_{t+h}) \quad (7)$$

$$\hat{V}(\mathbf{z}_t) := (1 - \lambda) \left[\sum_{h=1}^{H-t-1} \lambda^{h-1} V_h(\mathbf{z}_t) \right] + \lambda^{H-t-1} V_H(\mathbf{z}_t) \quad (8)$$

$$\mathcal{L}_V(\psi) := \sum_{h=t}^{t+H} \left\| V_\psi(\mathbf{z}_h) - \hat{V}(\mathbf{z}_h) \right\|_2^2 \quad (9)$$

190 We use an ensemble of 3 critics to reduce variance. To enable FoG optimization, it is important to use
 191 a well-regularized world model. We use the $(E_\phi(\mathbf{s}, \mathbf{e}), F_\phi(\mathbf{s}, \mathbf{a}, \mathbf{e}), R_\phi(\mathbf{s}, \mathbf{a}, \mathbf{e}))$ model proposed
 192 by TD-MPC2 [16] with learnable task embeddings \mathbf{e} . It is trained in an auto-regressive fashion by
 193 sampling data from a buffer with loss function:

$$\mathcal{L}_{wm}(\phi) = \mathbb{E}_{(\mathbf{s}, \mathbf{a}, r, \mathbf{s}', \mathbf{e}) \sim \mathcal{B}} \left[\sum_{t=0}^H \gamma^t (\|\mathbf{z}_{t+1} - sg(E_\phi(\mathbf{s}_{t+1}, \mathbf{e}))\|_2^2 + CE(\hat{r}_t, r_t)) \right] \quad (10)$$

194 where $sg(\cdot)$ is the stop-gradient operator and CE is the cross-entropy loss function. Reward prediction
 195 is formulated as a discrete regression problem in log-transformed space. Furthermore, E_ϕ and F_ϕ
 196 use SimNorm activation (Eq. 4) in their output layers. All trainable models are fully-connected MLPs
 197 with LayerNorm [3] and Mish activation [28]. The complete algorithm is shown in Algorithm 1.
 198 Further implementation details and hyper-parameters are listed in Appendix C.

199 5 Experimental results

200 5.1 Contact-rich single tasks

201 We first assess our proposed method on complex continuous control tasks with up to $\mathcal{A} = \mathbb{R}^{152}$ using
 202 the differentiable simulator dflex [44]. Hopper, Ant, Anymal, Humanoid and muscle-actuated (SNU)
 203 Humanoid (Figure 4) are tasked to maximize forward velocity ¹. We compare against SHAC [44],

¹While these tasks are inspired by dm_control [43], they are also fundamentally more challenging as they have to maximize an unbounded forward velocity, not achieve a velocity target.



Figure 4: High-dimensional single-task environments (left to right): Hopper, Ant, Anymal, Humanoid and SNU Humanoid. Our method successfully learns tasks with up to $m = 152$ continuous action dimensions. Additional 80 multi-task environments used in this paper are listed in Appendix E

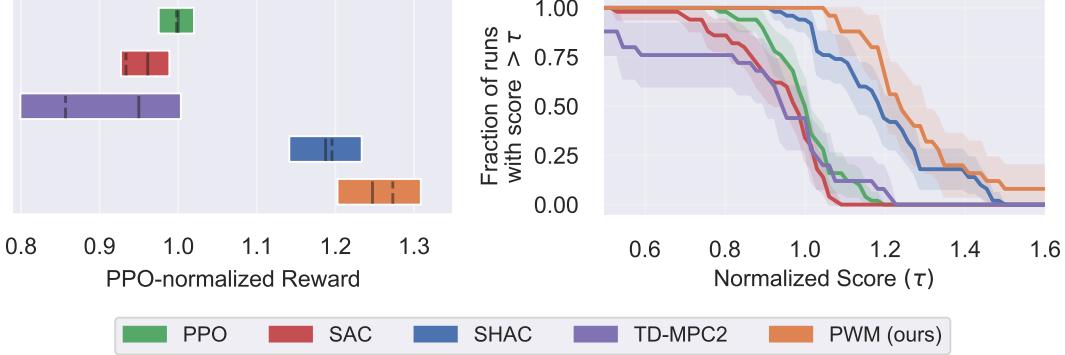


Figure 5: Aggregate results from high-dimensional locomotion tasks where each agent is trained to solve just that task (i.e. specialist). The **left** figure summarizes rewards achieved at the end of training using 50% IQM for the solid lines and 95% CI as suggested by [1], as well as mean for the dashed lines. We see that PWM achieves higher rewards than our main baselines TD-MPC2 and SHAC. The **right** figure shows score distributions across all tasks which lets us understand the performance variability of each approach. PWM exhibits a similar curve to SHAC but different than TD-MPC2, due to the policy learning approach.

204 a method with a similar actor-critic architecture but uses gradients directly from the differentiable
 205 simulation. This allows us to understand whether world models induce better landscapes for policy
 206 learning. Furthermore, we compare against TD-MPC2 which uses the same world model but learns a
 207 policy in a model-free fashion and actively plans at inference time. This comparison allows us to
 208 understand whether first-order gradients can learn better policies. We additionally include prominent
 209 model-free baselines PPO [39] and SAC [13]. TD-MPC2 follows the hyper-parameters from the
 210 original work [16], while all other baselines follow [44].

211 We conduct this experiment across 5 tasks with 5 seeds each where PWM and TD-MPC2 use the same
 212 pre-trained world models and are left to learn a policy and finetune their world models online. This is
 213 done to enable fair comparison to SHAC which directly has access to the simulation model and does
 214 not require any training. The results in Figure 5 reveal that (1) PWM is able to learn policies with
 215 higher reward than SHAC asymptotically, indicating that regularized world models induce smooth
 216 optimization landscapes than the true (discontinuous) dynamics. Furthermore (2) our method is able
 217 to learn policies with higher rewards than TD-MPC2 without the need for online planning and with
 218 the same compute time budget. However, PWM does not scale well to the highest dimensional task.
 219 More experiment details and results are included in Appendix D.

220 5.2 Multi-task world-model

221 We analyze the scalability of our proposed framework and method to large multi-task pre-trained
 222 world models. We evaluate on two settings: (1) 30 continuous control dm_control tasks [43] ranging
 223 from $m = 1$ to $m = 6$ and (2) 80 tasks which include 50 additional manipulation tasks from
 224 MetaWorld [47] with $n = 39$ and $m = 4$. These two multi-task settings were introduced as MT30 and
 225 MT80 by [16]. In conducting our experiments, we harness the same data and world model architecture
 226 as TD-MPC2. The data consists of 120k and 40k trajectories per dm_control and MetaWorld task,
 227 respectively generated by 3 random seeds of TD-MPC2 runs. The world models we use are the 48M
 228 parameter models introduced in [16].

229 To train PWM, we first pre-train the world models on the dataset in a similar fashion to TD-MPC2
 230 but with training $H = 16$ and $\gamma = 0.99$ for better first-order gradients as highlighted in Section 4.2.
 231 Then we train a PWM policy on each particular task using the offline datasets for 10k gradient steps
 232 which take 9.3 minutes on an Nvidia RTX6000 GPU. We evaluate task performance for 10 seeds for
 233 each task and aggregate results in Figure 6. We compare against TD-MPC2 which learns a multi-task
 234 policy while pre-training its world model and relies on online planning at inference. We can see
 235 that PWM learns behavior achieving higher reward than TD-MPC2 while also being significantly
 236 faster at inference time. We further compare our multi-task PWM policy to online-trained single-task
 237 experts SAC [13] and DreamerV3 [15]. Figure 6 reveals that multi-task PWM, while disadvantaged,
 238 performs comparably to the single-task experts without requiring any environment interaction and
 239 only training policies for ≤ 10 minutes per task. Additional results in Appendix E.

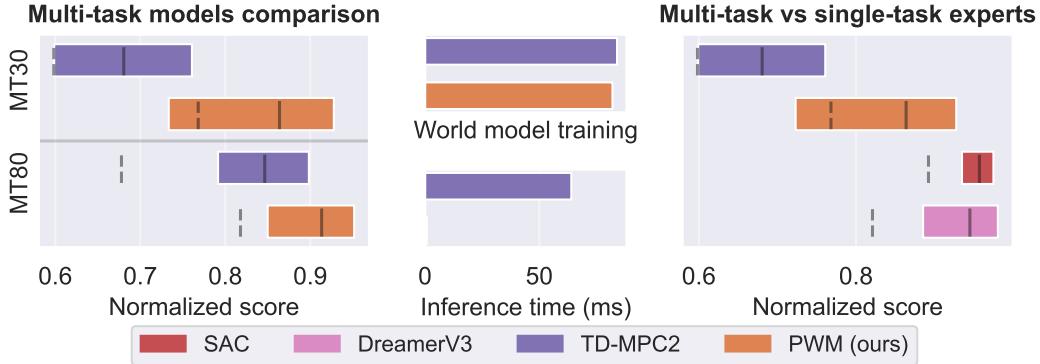


Figure 6: Multi-task results. The **left** figure shows results of multi-task agents in the 30 and 80 task set settings which include environments from dm_control [43] and MetaWorld [47]. The results show 50% IQM with the solid lines and mean with the dashed lines. The bars represent 95% CI. In both settings PWM achieves higher reward than TD-MPC2 without the need for online planning. The **middle** figure compares the training and inference times of TD-MPC2 and PWM for the 48M parameter model. We can see that PWM has significantly lower inference time as it does not use online planning. The **right** figure shows a comparison between multi-task PWM and single-task experts SAC and DreamerV3 on the MT30 task set. Notably, PWM is able to match the performance of SAC and DreamerV3 without requiring any environment interaction.

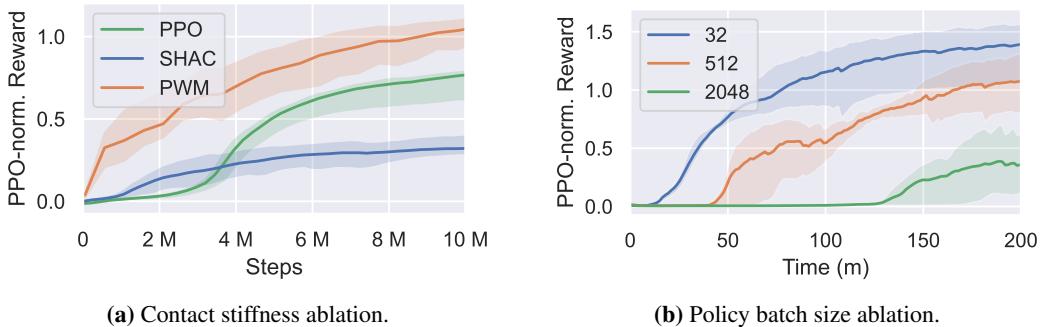


Figure 7: Left figure shows contact stiffness ablation where we increase contact stiffness on the Hopper task and analyze the effects on policy learning. The results indicate that stiff (but realistic) contact has adverse effects on SHAC which uses the simulation model to learn. Meanwhile, PPO and PWM remain unaffected with PWM still obtaining 17% more reward than PPO asymptotically. The **right figure shows a policy batch size ablation** on the Any task where we vary only the batch size used to train the policy components of PWM. Unfortunately we observe that PWM provides best result within a unit of time by using small batch sizes. Both figures show 50% IQM and 95% CI over 5 random seeds.

240 5.3 Ablations

- 241 We perform 4 ablations on the complex single task experiments in order to understand the nuances of
242 first-order optimization through world models with PWM.
243 We increase the **contact stiffness** to be more realistic but also more stiff contact gives gradients with
244 high sample error [40]. We run the same experiment as Section 5.1, but only for the Hopper task
245 and present the aggregate results from 5 random seeds in Figure 7a where we normalize rewards
246 by the maximum reward achieved by PPO in Section 5.1. We see that while PPO and PWM
247 rewards remain similar to prior results, while SHAC performance decreases by 48%. This shows
248 that regularized world models are robust to stiff contact models and thus more generalizable the
249 differentiable simulations.
250 The **second ablation explores batch sizes** for policy learning with first-order gradients. Contrary
251 to model-free methods which can scale to large batch sizes, we find that FoG techniques like PWM
252 benefit from smaller batch sizes. We explore this on the Ant task in Figure 7b where we plot 50%

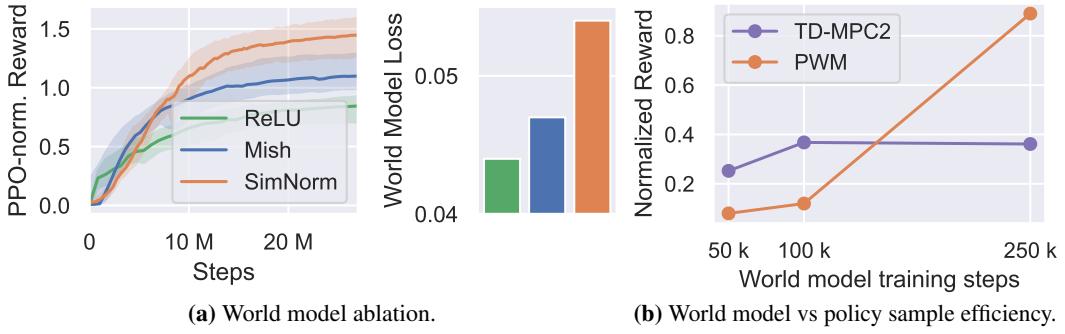


Figure 8: The left figure **ablates the activation functions** of the world model used to learn policies on the Ant task. We progressively add more regularization to the world model via changes to the activation function and observe an inverse correlation between world model loss and policy reward. This indicates that we should not construct world models for accuracy but for policy learning. The right figure **investigates the policy sample efficiency** on 5 dm_control tasks. We use the same data to pre-train world models for varying amount of gradient steps and then train the policy for 50k gradient steps and compare against TD-MPC2 (without planning). The results indicate that PWM policies are significantly more sample efficient but also require better trained world models. All results shown are 50% IQM with 95% CI across 5 random seeds.

253 IQM rewards over 5 random seeds. While larger batch sizes allow us to generate more data within a
254 unit of time, that does not necessarily translate to learning better policies.

255 Next we **ablate the world model regularization**. We perform the same experiment as Section 5.1 on
256 the Ant task but now pre-train 3 different world models. (1) with ReLU activation func., (2) with
257 Mish activation func. and (3) with Mish activation func. and SimNorm activation func. at the output
258 layers of E_ϕ and F_ϕ . Figure 8a reveals that while less regularization results in lower world model
259 error, that does not translate to learning better policies. Surprisingly, less regularized world models
260 enable policies to start faster (up to 1M steps) but plateau to a suboptimal policy.

261 To understand the **policy sample efficiency** of PWM while controlling for the world model, we
262 perform an ablation where we pre-train the same world model for [50k, 100k, 250k] gradient steps
263 on an offline dataset. Then we fix the world model and train only the policy components on the
264 same dataset for 50k gradient steps and measure the reward. We do this for 3 random seeds and 5
265 dm_control tasks. We repeat the same experiment for TD-MPC2 but disable its planning component
266 in order to understand the learning dynamics of each methods’ policy components. The results
267 in Figure 8b show that the PWM policy components are significantly more sample efficient than
268 TDMPC2 but also require better trained world models in order to obtain high reward.

269 6 Conclusion

270 In this work, we introduced Policy learning with large World Models (PWM), a novel MBRL approach
271 that utilizes large multi-task world models as differentiable physics simulators for efficient policy
272 training using First-order Gradients (FoG). Our evaluations demonstrated that PWM can learn policies
273 with higher rewards than existing methods, even if they have access to simulation ground-truth models.
274 Furthermore, the PWM framework paves a pathway to scalably learn high-performing policies from
275 large multi-task world models, achieving higher rewards than our main baseline TDMPC2 without
276 the need for online planning.

277 **Limitations.** Despite its demonstrated efficacy, PWM has notable limitations. Firstly, performance
278 relies heavily on the availability of substantial pre-existing data to train the world model, which might
279 not always be feasible, especially in novel or low-data environments. Secondly, although PWM
280 facilitates fast and cost-effective policy training, it necessitates re-training for each new task, which
281 could limit its applicability in scenarios requiring rapid adaptation to diverse tasks. Lastly, the current
282 TDMPC2 world models used are difficult to train at scale due to their autoregressive formulation.

283 In summary, PWM pushes the boundaries of multi-task policy learning from world models. Future
284 research directions can explore learning from images and

285 **A closing remark on societal impact.** Our proposed method and contributions are foundational
286 in nature and not likely to have any immediate negative societal impact or risks. However, we
287 acknowledge that embodied AI agents in general pose substantial challenges to society, including
288 but not limited to: disruption of the labor market, safe and reliable deployment of robots alongside
289 humans, and potential for misuse by bad actors.

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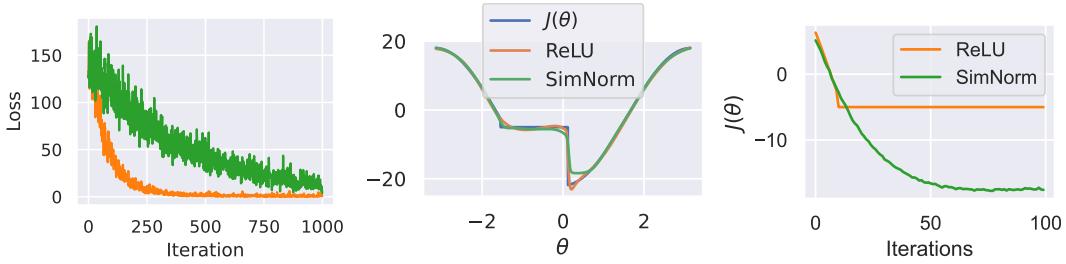


Figure 10: Extended ball-wall toy example results. The left figure shows the model losses as they are trained to approximate the target function $J(\theta)$. The middle figure shows the output of the trained model across the spectrum of θ as well as the true target. This is the function we attempt to minimize in the right figure. We can see that when using the MLP with ReLU activation functions, the optimizer quickly gets stuck in local minima while the model using SimNorm activation function is able to find a solution closer to the true one.

421 A Ball-wall example details

422 This section provides more details on the ball-wall example used to showcase the issues of optimizing
 423 through contact in Section 4.1. In constructing this toy example we chose a simple physical system
 424 that exhibits contact discontinuities. Inspired by Suh et al. [40], we constructed a simple problem
 425 of a point mass (ball) being thrown forward (x direction) at a fixed velocity v . The optimization
 426 parameter of interest is the initial angle θ and the goal is to maximize forward distance traveled (in
 427 2D). For simplicity we assume that the ball sticks to the wall (without complex contact) which can be
 428 expressed as:

$$x = f(\theta) = \begin{cases} x_0 + v \cos(\theta)t + \frac{1}{2}gt^2 & \text{if } y_{\text{contact}} > h \\ w & \text{else} \end{cases} \quad (11)$$

429 where $g = 9.81$ is gravity, h and w are the height and width of the wall, (x_0, y_0) is the starting
 430 position, $v = 10$ is the starting velocity and $t = 2$ is time. y_{contact} is the height at the time of contact
 431 t_{contact} which are both given by solving Eq. 11 for $f(\theta) = w$:

$$t_{\text{contact}} = \frac{-v \cos(\theta) + \sqrt{v^2 \cos^2(\theta) + aw}}{a} \quad y_{\text{contact}} = y_0 + v \sin(\theta)t + \frac{1}{2}gt^2$$

432 We visualize the toy example in Figure 9 to aid reading. With
 433 $f(\theta)$ defined, we attempt to learn it with two Multi-Layer Per-
 434 ceptrons (MLPs). We configure them to have 2 hidden layers
 435 of 32 neurons each. The first MLP uses ReLU activation func-
 436 tions, while the latter uses SimNorm activation functions as
 437 defined in Eq. 4. Both models are initialized with identical
 438 random parameters and are trained with the ADAM optimizer
 439 with learning rate $\alpha = 2 \times 10^{-3}$ for 100 epochs using a batch
 440 size of $B = 50$. The data we use to train the models was 1000
 441 uniform samples of $f(\theta)$ within $\theta \in [-\pi, \pi]$. Figure 9 shows
 442 the training losses of the models, induced optimization land-
 443 scapes and the losses when attempting to maximize the models
 444 as you would do in an RL setting.

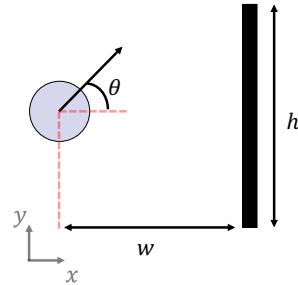


Figure 9: Pedagogical ball-wall toy problem visualized.

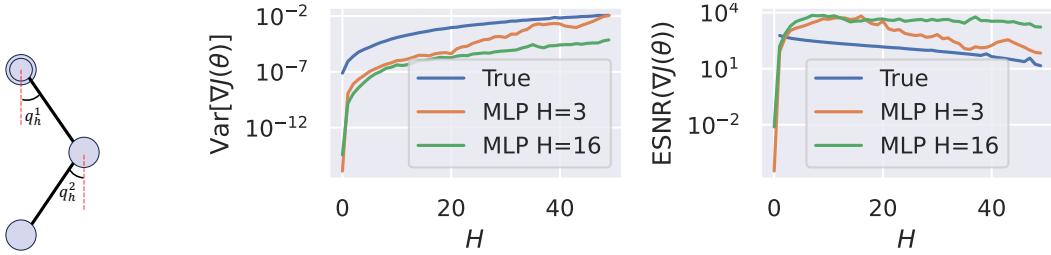


Figure 11: Double pendulum pedagogical example. The middle figure evaluates the variance of policy gradient estimates over $N = 100$ Monte-Carlo samples for varying horizons H . The right figure shows the same data but plots the Expected Signal-to-Noise ratio (ESNR) with higher values translating to more useful gradients. These results suggest that world models trained over long horizon trajectories provide more useful gradients.

445 B Double pendulum example details

446 The double pendulum (also known as Acrobot [31]) is a classic
 447 under-actuated chaotic system. It is characterized by its sensitivity to initial conditions where even
 448 small perturbations result in large gradient variance with long horizon (> 20) trajectories. We chose
 449 this system to analyze variance and expected signal-to-noise ratio (ESNR) in Section 4.2 as it is the
 450 easiest problem exhibiting chaosness. We model this toy problem similar to DMControl [43] in our
 451 differentiable simulator, dflex as we need ground truth gradients for comparison. The first link with
 452 angle θ_1 is fixed to the base and not actuated. The second link with angle θ_2 is the only control input
 453 via $\dot{\theta}_2$. The state of the system is calculated as:

$$s = [\cos(\theta_1), \sin(\theta_1), \cos(\theta_2), \sin(\theta_2), \dot{\theta}_1, \dot{\theta}_2]$$

454 The objective of this toy example is to bring and balance the pendulum upwards which we achieve by
 455 formulating a reward:

$$r(s, a) = -\theta_1^2 - \theta_2^2 - 0.1\dot{\theta}_2^2$$

456 Next we train world models to approximate the dynamics and reward above. For this we collect
 457 data with the SHAC algorithm [44] over 3 different runs for a total of 24,000 episodes of length 240
 458 timesteps. Maximum episode reward achieved during data collection was -942.95. Then we train two
 459 TDMPC2 [16] world models on the collected data. We use the 5M parameter model which features a
 460 latent state of dimension of 512, encoder E_ϕ with one hidden dimension of 256, dynamics model
 461 MLP with 2 hidden layers with 512 neurons and a rewards model of the same design. We keep the
 462 same hyper-parameters as per the origin work by Hensen et al. but use $\gamma = 0.99$ which we found
 463 to reduce variance substantially. We train two models with different training horizons $H = 3$ and
 464 $H = 16$ for 100k batch samples and a batch size of 1024.

465 With the trained models, we now compare the variance of stochastic gradients provided by the true
 466 dynamics of the simulation and the two trained models. We do this by loading the best policy learned
 467 by SHAC during data collection and executing a $H = 50$ rollout across the 3 models. We ensure
 468 that the same actions are taken for each evaluated models and collect 100 Monte Carlo samples. In
 469 addition to variance, we report ESNR as suggested by [34] and defined in 5. Higher ESNR translate
 470 to more useful gradients and we naturally should expect values to decrease with increased H . We
 471 reported the results in Figure 3 but also duplicate them in Figure 11 for convenience and ease of
 472 reading.

473 **C Implementation details and hyper-parameters**

474 The section details several implementation details of PWM that we thought are not crucial for
 475 understanding the proposed approach in Section 4.3 but are important for replicating the results.

- 476 1. **Reward binning** - the reward model we use in PWM is formulated as a discrete regression
 477 problem where \mathbb{R} rewards are discretized into a predefined number of bins. Similar to
 478 [16, 25], we do this to enable robustness to reward scale and multi-task-ness. In particular, we
 479 perform two-hot encoding using SymLog and SymExp operators which are mathematically
 480 defined as:

$$\text{SymLog}(x) = \text{sign}(x) \log(1 + |x|) \quad \text{SymExp}(x) = \text{sign}(x)(e^{|x|} - 1)$$

481 Two-hot encoding is then performed with:

```
482     def two_hot(x):
483         x = clamp(symlog(x), vmin, vmax)
484         bin_idx = floor((x - vmin) / bin_size)
485         bin_offset = (x - vmin) / bin_size - bin_idx
486         soft_two_hot = zeros(x.size(0), num_bins)
487         soft_two_hot[bin_idx] = 1 - bin_offset
488         soft_two_hot[bin_idx + 1] = bin_offset
489         return soft_two_hot
```

492 Inverting this operation to get back to scalar rewards would usually involve $\text{SymExp}(x)$
 493 but note that the $\text{sign}(x)$ operator is not differentiable and would therefore not work for
 494 FoG. Instead, we chose to omit the $\text{SymExp}(x)$ operation which technically now returns
 495 pseudo-rewards but also gradients which we found sufficient for policy learning:

```
496     def two_hot_inversion(x):
497         vals = linspace(vmin, vmax, num_bins)
498         x = softmax(x)
499         x = torch.sum(x * vals, dim=-1)
500         return x
```

- 503 2. **Critic training** - while Algorithm 1 function to similar results as presented in 5, we found
 504 it beneficial to split the critic training data from a single rollout into several smaller mini-
 505 batches and over them for multiple gradient steps. In our implementation we split the data
 506 into 4 mini-batches and perform 8 gradient steps over them with uniform sampling. With a
 507 $H = 16$ and batch size 64, this translates to a critic batch size of 256.
- 508 3. **Minimum policy noise** - Due to the larger amount of gradient steps needed, we noticed
 509 that PWM’s actor tends to collapse to a deterministic policy rapidly. As such, we found it
 510 beneficial to include a lower bound on the standard deviation of the action distribution in
 511 order to maintain stochasticity in the optimization process. We have used 0.24 throughout
 512 this paper. While similar results would be possible by adding an entropy term [39], we
 513 found our current solution sufficient
- 514 4. **World model fine-tuning** - Throughout all of our experiments we found that the offline
 515 data used to train PWM’s world model to be crucial to learning a good policy. In very
 516 high-dimensional tasks such as Humanoid SNU, collecting extensive data is a difficult task.
 517 As such, in these tasks we found it beneficial to online fine-tune the world model. We do
 518 this on all single-task experiments of Section 5.1 using the default hyper-parameters and a
 519 replay buffer of size 1024.

520 **D Contact-rich single task experiment details**

521 In Section 5.1, we explore 5 locomotion tasks with increasing complexity. They are described below
 522 and shown in Figure 4.

- 523 1. **Hopper**, a single-legged robot jumping only in one axis with $n = 11$ and $m = 3$.
- 524 2. **Ant**, a four-legged robot with $n = 37$ and $m = 8$.

Hyper-parameter	Value
Policy components	
Horizon (H)	16
Batch size	64
α_θ	5×10^{-4}
α_ψ	5×10^{-4}
Actor grad norm	1
Critic grad norm	100
Actor hidden layers	[400, 200, 100]
Critic hidden layers	[400, 200]
Number of critics	3
λ	0.95
γ	0.99
Critic batch split	4
Critic iterations	8
World model components (48M)	
Latent state (z) dimension	768
Horizon (H)	16
Batch size	1024
α_ϕ	3×10^{-4}
World model grad norm	20.0
SimNorm V	8
Reward bins	101
Encoder E_ϕ hidden layers	[1792, 1792, 1792]
Dynamics F_ϕ hidden layers	[1792, 1792]
Reward R_ϕ hidden layers	[1792, 1792]
Task encoding dimension	96

Table 1: Table of hyper-parameters used in PWM, shared across all tasks.



Figure 12: Locomotion environments (left to right): Hopper, Ant, Anymal, Humanoid and SNU Humanoid.

- 525 3. **Anymal**, a more sophisticated quadruped with $n = 49$ and $m = 12$ modeled after [20].
 526 4. **Humanoid**, a classic contact-rich environment with $n = 76$ and $m = 21$ which requires extensive
 527 exploration to find a good policy.
 528 5. **SNU Humanoid**, a version of Humanoid lower body where instead of joint torque control, the
 529 robot is controlled via $m = 152$ muscles intended to challenge the scaling capabilities of algorithms.
 530 All tasks share the same common main objective - maximize forward velocity v_x :
 531 We additionally use auxiliary rewards R_{height} to incentivise the agent to, R_{angle} to keep the agents'
 532 normal vector point up, $R_{heading}$ to keep the agent's heading pointing towards the direction of
 533 running and a norm over the actions to incentivise energy-efficient policies. For most algorithms,
 534 none of these rewards apart from the last one are crucial to succeed in the task. However, all of them
 535 aid learning policies faster.

$$R_{height} = \begin{cases} h - h_{term} & if h \geq h_{term} \\ -200(h - h_{term})^2 & if h < h_{term} \end{cases}$$

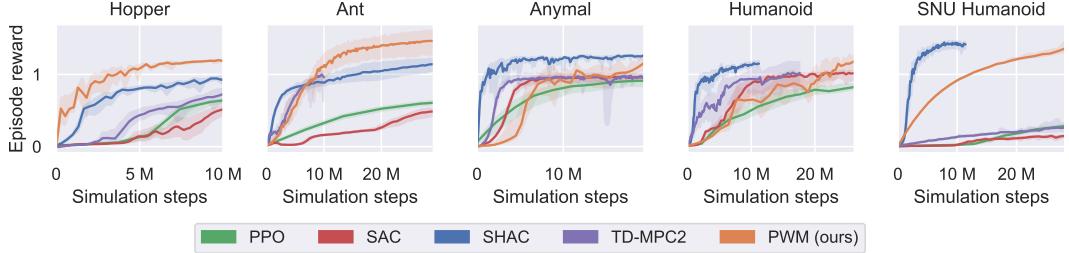


Figure 13: Learning curves for each environment. This figure shows 50% IQM and 95% CI across 5 random seeds for each task in the dflex simulation suite. Rewards are normalized by the maximum reward achieved by PPO (usually ≥ 100 M steps). While PWM remains competitive with SHAC for most tasks, it does not scale well to the 152 action dimension SNU Humanoid.

Environment	Reward
Hopper	$v_x + R_{height} + R_{angle} - 0.1\ \mathbf{a}\ _2^2$
Ant	$v_x + R_{height} + 0.1R_{angle} + R_{heading} - 0.01\ \mathbf{a}\ _2^2$
Anymal	$v_x + R_{height} + 0.1R_{angle} + R_{heading} - 0.01\ \mathbf{a}\ _2^2$
Humanoid	$v_x + R_{height} + 0.1R_{angle} + R_{heading} - 0.002\ \mathbf{a}\ _2^2$
Humanoid STU	$v_x + R_{height} + 0.1R_{angle} + R_{heading} - 0.002\ \mathbf{a}\ _2^2$

Table 2: Rewards used for each task bench-marked in Section 5

$$R_{angle} = 1 - \left(\frac{\theta}{\theta_{term}} \right)^2$$

536 $R_{angle} = \|\mathbf{q}_{forward} - \mathbf{q}_{agent}\|_2^2$ is the difference between the heading of the agent \mathbf{q}_{agent} and the
 537 forward vector \mathbf{q}_{agent} . h is the height of the CoM of the agent and θ is the angle of its normal vector.
 538 h_{term} and θ_{term} are parameters that we set for each environment depending on the robot morphology.
 539 Similar to other high-performance RL applications in simulation, we find it crucial to terminate
 540 episode early if the agent exceeds these termination parameters. However, it is worth noting that
 541 AHAC is still capable of solving all tasks described in the paper without these termination conditions,
 542 albeit slower.

543 All results presented in Figure 13 are for 5 random seeds using the simulator in a vectorized fashion
 544 with 64 parallel environments for all approaches, except PPO which uses 1024. We note that while
 545 simulation steps appear high, all of these experiments are executed ≤ 2 hours on an Nvidia RTX6000
 546 GPU. In addition to the learning curves of Figure 13, we also present tabular results below:

	Hopper	Ant	Anymal	Humanoid	SNU Humanoid
PPO	1.00 ± 0.11	1.00 ± 0.12	1.00 ± 0.03	1.00 ± 0.05	1.00 ± 0.09
SAC	0.87 ± 0.16	0.95 ± 0.08	0.98 ± 0.06	1.04 ± 0.04	0.88 ± 0.11
TDMPC2	0.85 ± 0.37	1.0 ± 0.49	0.98 ± 0.48	1.03 ± 0.45	0.26 ± 0.12
SHAC	1.02 ± 0.03	1.16 ± 0.13	1.26 ± 0.04	1.15 ± 0.04	1.44 ± 0.08
PWM	1.20 ± 0.29	1.46 ± 0.31	1.16 ± 0.24	1.19 ± 0.025	1.08 ± 0.24

Table 3: Tabular results of the asymptotic rewards achieved by each algorithm across all tasks. The results presented are PPO-normalised 50 % IQM and standard deviation across 5 random seeds. Most algorithms have been trained until convergence.

547 We note that TDMPC2 and PWM use pre-trained world models on 20480 episodes of each task. The
 548 world models are trained for 100k gradient steps and the same world models (specific to each task)
 549 are loaded into both approaches. The data consists of trajectories of varying policy quality generated
 550 with the SHAC algorithm. Trajectories include near-0 episode rewards as well as the highest reward
 551 achieved by SHAC. Note that we also run an early termination mechanism in these tasks which is
 552 done to accelerate learning and iteration.

	Hopper	Ant	Anymal	Humanoid	SNU Humanoid
PPO	4742 \pm 521	6605 \pm 793	12029 \pm 360	7293 \pm 365	4114 \pm 370
SAC	4126 \pm 759	6275 \pm 528	11788 \pm 722	7285 \pm 292	3620 \pm 453
TDMPC2	4027 \pm 1768	6591 \pm 2708	11787 \pm 4702	7476 \pm 3268	1121 \pm 525
SHAC	4837 \pm 142	7662 \pm 859	15157 \pm 481	8387 \pm 292	5924 \pm 329
PWM	5680 \pm 2303	9672 \pm 2012	13927.74 \pm 2882	8661 \pm 1792	4585 \pm 958

Table 4: Tabular results of the asymptotic (end of training) rewards achieved by each algorithm across all tasks. The results presented are 50 % IQM and standard deviation across 10 random seeds. All algorithms have been trained until convergence.

553 E Multi-task experiments additional results

554 In this section we provide additional results on multi-task experiments. While we find it beneficial
 555 to train the world model at the same horizon as the policy learning, it is not strictly necessary to
 556 achieve good performance. In Figure 14 we present an ablation where we compare PWM world
 557 models pre-trained on horizons $H = 3$ and $H = 16$ and policies trained only with $H = 16$. These
 558 results reveal that $H = 16$ trained world models have only marginally higher scores. On deeper
 559 inspection, most of increased scores come from dm_control tasks which are harder than MetaWorld
 560 tasks on average. Therefore if training new world models, we advise using higher H ; however if
 561 other pre-trained world models exist with suboptimal H , they will probably be also useful.

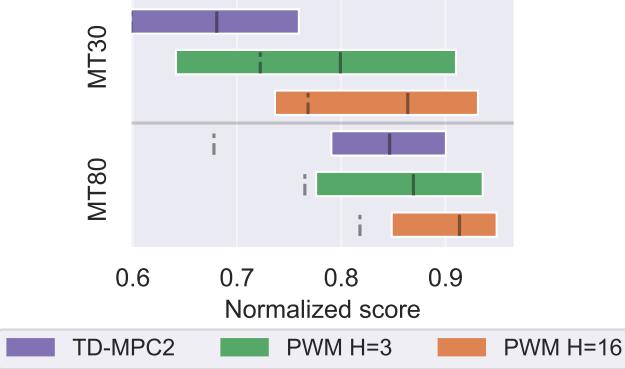


Figure 14: Horizon ablation of the world model

562 Figures 15 and 16 give scores for individual tasks for TDMPC2 and PWM across both the MT30 and
 563 MT80 task sets. We can observe that most of the increased performance of PWM is in dm_control
 564 tasks which are on average more difficult than MetaWorld.

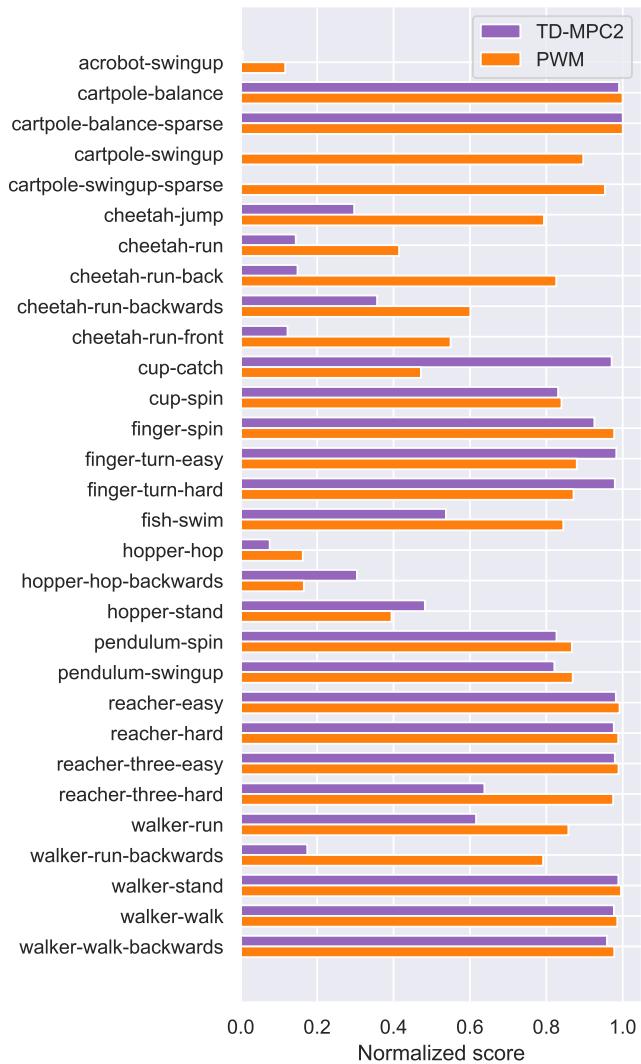


Figure 15: Individual task results for MT30 task set.

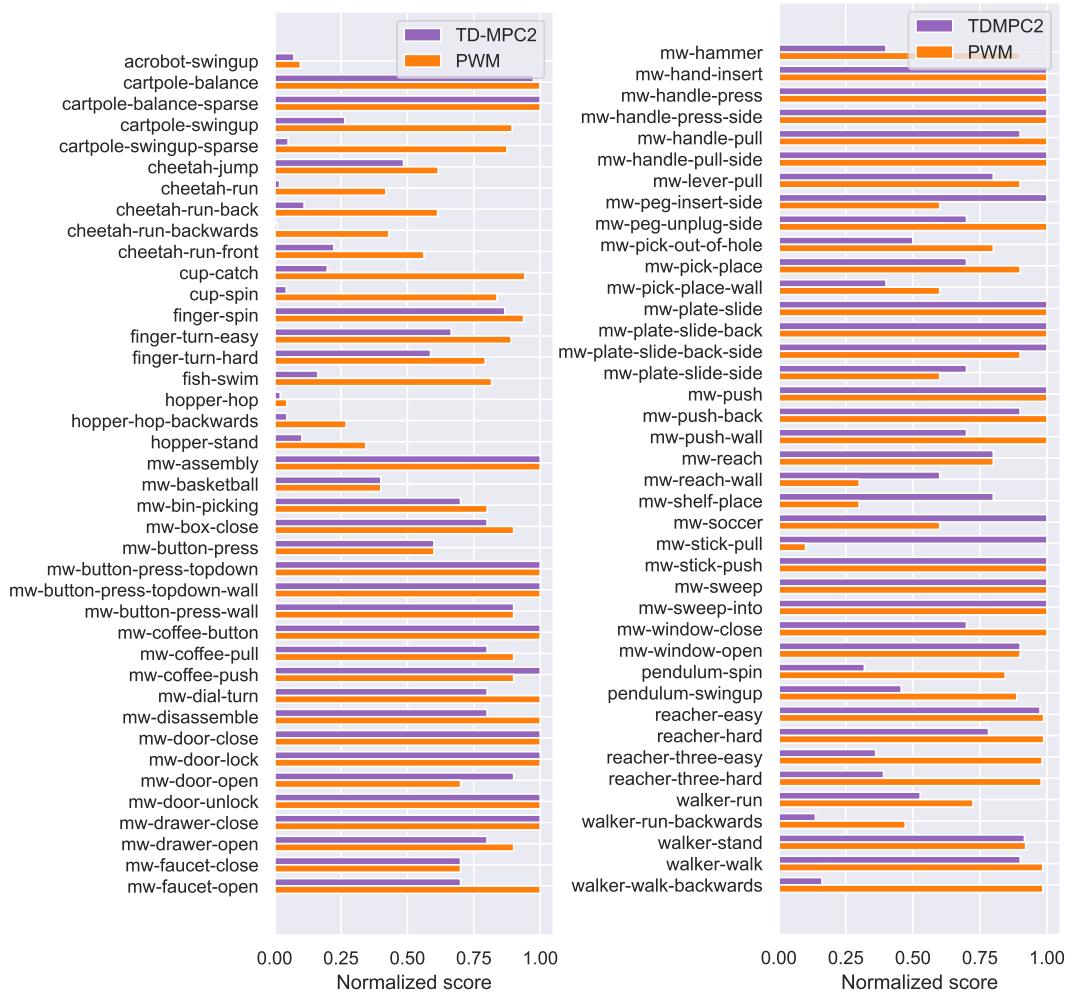


Figure 16: Individual task results for MT80 task set.

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