Learning to Drive Small Scale Cars from Scratch

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Abstract: We consider the problem of learning to drive low-cost small scale cars using reinforcement learning. It is challenging to handle the long-tailed distributions of events in the real-world with handcrafted logical rules and reinforcement learning could be a potentially more scalable solution to deal with them. We adopt an existing platform called Donkey car for low-cost repeatable and reproducible research in autonomous driving. We consider the task of learning to drive around a track, given only monocular image observations from an on-board camera. We demonstrate that the soft actor-critic algorithm combined with state representation learning using a variational autoencoder can learn to drive around randomly generated tracks on the Donkey car simulator and a real-world track using the Donkey car platform. Our agent can learn from scratch using sparse and noisy rewards within just 10 minutes of driving experience.

Keywords: Autonomous driving, Reinforcement learning

1 Introduction

Autonomous driving is an active area of research with dramatic progress in recent years and could play a major role in the future of transportation systems, due to increased safety and efficiency. Advanced control systems with a certain degree of autonomy are already available in consumer cars. A key challenge in this area has been the difficulty in incorporating the ability to handle rare unseen situations as they follow a very long-tailed distribution. A typical autonomous driving stack consists of different modules for perception and control [1]. Perception modules such as object detectors require a significant amount of labeled data for training and it is difficult to collect training data that covers all rare situations. The driving stack also consists of several handcrafted logical rules to separately deal with different situations that it might encounter. Alternatively, learning the whole autonomous driving stack in an end-to-end fashion offers a potentially more scalable way of achieving better autonomy. Recent works have successfully used imitation learning to train agents by imitating the actions of a human driver [2]. While this approach has proven effective and easy to train, it requires a significant amount of data to train and does not generalize well to out-of-distribution situations.

In this work, we consider autonomous driving as a reinforcement learning problem. Reinforcement learning (RL) has been successfully applied to learn high performance agents in games [3], robotics [4], and other challenging problems [5]. A reinforcement learning approach requires less manual supervision and could potentially generalize well to deal with rare out-of-distribution situations. Kendall et al. [6] has successfully demonstrated the use of deep RL to learn to drive a full-sized car.

In this paper, we consider small-scale remote-controlled (RC) electric cars for low-cost repeatable and reproducible academic research in autonomous driving. There are very many kinds of small-scale RC electric cars. We consider RC cars that primarily consists of a chassis holding a small but powerful electric motor for throttle, an electric speed control (ESC) to control the speed of this motor, a servo for steering, and batteries to power them. Despite their small size, RC cars can be very fast and can drive off-road on various terrains.

We propose to use an existing platform called Donkey car [7] for low-cost research in autonomous driving. Donkey car is an open-source self-driving platform for small-scale RC cars. A Donkey car requires minimal hardware costing $\sim250$ and takes 2 hours to assemble. Similar cars can be easily built by modifying easily available RC cars, with minimal hardware requirements (see http:}
Figure 1: Our Donkey car. The back wheels are throttled using a brushless motor and the front wheels are steered using a servo. The Raspberry Pi, a camera sensor and other supporting hardware are mounted on a 3D printed cage.

Figure 2: Screenshot of the Donkey car simulator. The physics and graphics of the simulator are based on the Unity game simulator. The simulated car matches the real platform and the task is to train it to follow lanes on randomly generated roads.

//docs.donkeycar.com/). It is also possible to buy ready-made kits consisting of all components required to build a Donkey car. The Donkey car platform is supported by an active community that maintains the supported hardware configurations and software packages. There are also regular meetups and races organized all around the world by Donkey car enthusiasts.

The standard Donkey car platform primarily consists of an RC car mounted with a wide-angle camera sensor, a Raspberry Pi and supporting hardware to control the car (see Figure 1). The Donkey car platform is enhanced by a high-level modular Python package that enables fast experimentation. The Donkey Car platform has out-of-the-box support for various sensors (such as cameras, lidar, odometers, and GPS), actuators, and remote controllers (such as web-based or joysticks). The Donkey car software also comes with simple lane following agents and some behavioral cloning agents. All Donkey cars are calibrated after assembly so that the control dynamics of all Donkey cars are similar to a certain degree. The Donkey car community also maintains a Donkey car simulator based on the Unity game platform (see Figure 2). The simulator is wrapped in a convenient OpenAI Gym interface [8] and can be used for rapid experimentation of autonomous driving algorithms on randomly generated tracks before trying it on the real platform.

Learning to drive a Donkey car is challenging as we solely rely on a low-resolution RGB sensor to control a fast brushless motor, a challenging setting even for humans to drive. We adapt the Donkey car as a platform for low-cost research in autonomous driving. We learn to drive the car by remotely controlling it over an internet connection. We identify the various challenges of applying RL algorithms to the Donkey car platform and describe a repeatable and reproducible experimental setup in Section 5. We combine the soft actor-critic algorithm with state representation learning using a variational autoencoder to demonstrate that the algorithm can efficiently learn to drive in the simulator in Section 6 and with the real car in Section 7.

2 Related Work

We cast the autonomous driving problem as a reinforcement learning problem and use the state-of-the-art soft actor-critic (SAC) algorithm [9, 10]. SAC has been successfully applied to various robotic control problems [11, 12, 13]. We rely on just the on-board RGB camera for learning to drive. It is challenging to learn to drive directly from high dimensional image observations. We use a variational autoencoder (VAE) [14] to learn low-dimensional state representations of these images, which can be fed into the RL algorithm. We jointly optimize the VAE along with the policy and value networks of the SAC algorithm. Past works have unsuccessfully attempted to perform joint representation learning of VAEs in RL [15, 16, 17]. Similar to recent works [18, 19], we demonstrate stable joint representation learning by truncating the gradients to the VAE encoder.
from the actor loss. Auxiliary tasks such as the reconstruction of observations have been previously used to improve the performance of RL algorithms [20]. In some applications such as autonomous driving, it is possible to easily collect sensor measurements from a car before reinforcement learning and we investigate the possibility of unsupervised pretraining of the VAE using such data [15].

Learning to drive a full-sized car by following an obstacle-free GPS trajectory was considered as a reinforcement learning problem by Riedmiller et al. [21]. This was recently extended to handle image observations and sparse rewards by Kendall et al. [6]. While [6] also use VAE for state representation learning, they train it from just five episodes of random actions. We found that this leads to data collected only from a portion of the track and this does not generalize well to other parts of the track, which may contain other noisy objects. We show that joint learning of V AE with RL leads to more stable and better performance. We found the DDPG reinforcement learning algorithm used in [6] to be brittle with hyperparameter choices [22] and SAC to be more robust. We propose a small scale RC car platform called Donkey car as a low-cost alternative for research on autonomous driving. Full-sized cars such as the one used in [6] consist of high-resolution cameras, odometers, and PID controllers for precise control of the speed of the vehicle. Learning to drive using the low-resolution camera and highly sensitive throttle of a Donkey car brings it’s own challenges to reinforcement learning. Raffin and Sokolov [23] report some preliminary results on learning to drive in the Donkey car simulator.

3 Reinforcement Learning

In this section, we formulate the autonomous driving problem as a Markov decision process (MDP) and introduce the soft actor-critic (SAC) algorithm [10] used in this paper. An MDP consists of:

- a finite set of states $\mathcal{S}$,
- a finite set of actions $\mathcal{A}$,
- a transition probability function $s_{t+1} \sim p(\cdot | s_t, a_t)$ that represents the probability of transitioning to state $s_{t+1} \in \mathcal{S}$ by taking action $a_t \in \mathcal{A}$ in state $s_t \in \mathcal{S}$ at timestep $t$,
- a reward function $R(s_t, a_t)$ that provides a scalar reward for taking action $a_t$ in state $s_t$,
- a discount factor $\gamma \in [0, 1]$ to specify the importance of future rewards.

The goal of reinforcement learning is to learn a policy function $a_t \sim \pi(\cdot | s_t)$ that maximizes expected cumulative rewards $\mathbb{E} \left[ \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) \right]$, such that $a_t \sim \pi(\cdot | s_t)$ and $s_{t+1} \sim p(\cdot | s_t, a_t)$. We use the state-of-the-art soft actor-critic (SAC) algorithm in this paper. SAC is an off-policy RL algorithm that learns a stochastic actor to maximize an entropy-regularized version of the RL objective that also jointly maximizes the entropy of the learned policy:

$$
\mathbb{E} \left[ \sum_{t=0}^{\infty} \gamma^t \left( R(s_t, a_t) + \alpha \mathcal{H}(\pi(\cdot | s_t)) \right) \right],
$$

where $\alpha > 0$ is the temperature parameter to balance the joint optimization of the cumulative rewards and the entropy. At each iteration, SAC performs policy evaluation and policy iteration steps. The policy evaluation step involves approximating the $Q(s_t, a_t)$ function defined as the expected cumulative rewards obtained by taking action $a_t$ in state $s_t$ and then following policy $\pi$ thereafter. The Q-function for the entropy-regularized RL objective (called soft Q-function) is defined as:

$$
Q(s, a) = \mathbb{E} \left[ \sum_{t=0}^{\infty} \gamma^t \left( R(s_t, a_t) + \alpha \mathcal{H}(\pi(\cdot | s_t)) \right) \middle| s_0 = s, a_0 = a \right].
$$

The soft Q-function with parameters $\theta_Q$ is trained using transitions sampled from a replay buffer $\mathcal{D}$ to minimize the soft Bellman residual:

$$
J_Q(\theta_Q) = \mathbb{E}_{(s_t, a_t, r_t, s_{t+1}) \sim \mathcal{D}} \left[ (Q_{\theta_Q}(s_t, a_t) - r_t - \gamma V(s_{t+1}))^2 \right],
$$

where $r_t$ is the reward obtained at timestep $t$ and the soft value function $V(s_t)$ is the expected cumulative rewards obtained by following policy $\pi$ from state $s$ and is approximated using a Monte Carlo estimate based on the following relation:

$$
V(s_t) = \mathbb{E}_{a_t \sim \pi(\cdot | s_t)} \left[ Q_\theta(s_t, a_t) - \alpha \log \pi(a_t | s_t) \right].
$$
The policy improvement step involves updating the parametric policy function with parameters $\theta_\pi$ to minimize the KL divergence between the policy and the Boltzmann distribution induced by the Q-function using the following objective:

$$J_\pi(\theta_\pi) = \mathbb{E}_{s_t \sim D} \left[ \mathbb{E}_{a_t \sim \pi_{\theta_\pi}(\cdot|s_t)} \left[ \alpha \log(\pi_{\theta_\pi}(a_t|s_t)) - Q_{\theta}(s_t, a_t) \right] \right]$$

4 State Representation Learning

The only sensor that we use in this work is a wide-angle RGB sensor. Directly learning a policy from these raw images might be challenging. The policy and Q-functions of the agent are trained solely based on the sparse rewards signals and learning a good state representation from this could be sample-inefficient and unstable. Unsupervised training methods such as convolutional autoencoders can be used to learn low-dimensional representations of images, which can be fed into the RL algorithm. A convolutional autoencoder consists of a convolutional encoder $f_{\theta}$ that maps raw images $s_t$ to a low-dimensional latent representation $z_t$, and a deconvolutional decoder $g_{\theta}$ that reconstructs the original image $s_t$ from the latent representation $z_t$.

In this work, we use a variational autoencoder (VAE) [14] to learn latent representations of the images encountered by an agent. In VAEs, the latent representation space is stochastic and is often chosen to be a multivariate Gaussian distribution with a diagonal covariance matrix. The encoder outputs the mean $\mu_{\theta_f}(s_t)$ and variance $\sigma^2_{\theta_f}(s_t)$ parameters of the latent distribution $q_{\theta_f}(z_t|s_t) = \mathcal{N}(\mu_{\theta_f}(s_t), \sigma^2_{\theta_f}(s_t))$ and the decoder reconstructs the original image $s_t$ based on a sample from the latent distribution $z_t \sim q_{\theta_f}(\cdot|s_t)$. The encoder and decoder parameters are trained to maximize an objective of the form:

$$J_{\text{VAE}}(\theta_f, \theta_g) = \mathbb{E}_{s_t \sim D} \left[ \mathbb{E}_{z_t \sim q_{\theta_f}(\cdot|s_t)} \left[ \log p_{\theta_g}(s_t|z_t) \right] \right] - D_{\text{KL}}(q_{\theta_f}(z_t|s_t)||p(z_t)),$$

where the first term is the reconstruction loss and the second term acts as a regularizer. The latent representation vector $z_t$ can be used by an RL algorithm, instead of the raw image state $s_t$. The VAE can be pre-trained with some data before applying an RL algorithm or jointly optimized along with the policy and value networks. We found it important to update the VAE during the training of the RL algorithm. Images collected by a random or initial policy only includes images from the early part of a track and the VAE will not learn to reasonably represent the other parts of a track. Alternatively, it is possible to manually collect images from the whole track prior to training. Similar to previous works [18, 19], we find it stable to jointly optimize the VAE encoder parameters with the critic loss and the VAE loss, that is, we truncate the gradients from actor loss to the VAE encoder. Our agent architecture is illustrated in Figure 3.
5 Experimental Setup

In this section, we describe our experimental setup for learning to drive a Donkey car from scratch using reinforcement learning. We use a vanilla Donkey car platform assembled from the official Donkey car starter kit. The car is based on the HSP 94186 Brushed RC car, which has been fully tested to support the Donkey car platform. Besides the standard platform, we mount an extra 10,000 mAh battery onto the top cage, to power the Raspberry Pi. The standard kit uses the 1100 mAh car battery to power the Raspberry Pi, which leads to quick battery discharge and very short training times that are not feasible. A separate battery ensures that the car battery is only used when we power the motor and this enables longer training times.

Our experimental setup consists of the Donkey car and a GPU workstation. The car and the GPU workstation communicate with each other using a message queue over the Internet. The message queue is based on MQTT, a lightweight publish-subscribe messaging queue protocol that is run on top of the TCP/IP stack. The Donkey car uses the Donkey Python package to continuously run an observation loop where it sends the images from the wide-angle camera over the messaging queue. The training and inference of the reinforcement learning agent are performed on a GPU workstation which receives the images from the message queue and runs the policy to compute the raw actions to be taken at each step, which are sent to the car over the queue. We synchronize the whole control loop to run at a frequency of 10 Hz. The control loop always uses the latest available observation when computing the actions. We found that this setup could lead to aliasing effects if the observation frequency is also run at the same frequency of 10 Hz and there is a delay in the transmission of the latest image. We overcome this by running the observation loop at a higher frequency of 20 Hz.

In this paper, we consider the task of learning to consistently drive around a track, given only image observations from an on-board RGB camera. It is challenging to construct reward functions to achieve this. Auxiliary reward functions could take into account the distance traveled along the track and the speed of the car. However, the Donkey car platform does not have the sensors to reliably estimate them. We use a simple sparse reward that penalizes the agent for driving off the track. The agent receives a reward of 1 during every time-step until it drives off the track and penalty of -10 when it does so. The track we use in our real-world experiments is shown in Figure 4.

We use an episodic formulation of reinforcement learning. We collect data during each episode by just running the policy and storing the observations, actions, and rewards in a replay buffer. We train the VAE, policy, and value networks by sampling from the replay buffer at the end of each episode. Each episode starts with the car being at the same point in the track and is terminated when the car drives off the track. We use a simple mechanism to determine if the car has driven off the track (by thresholding out the darker track from the lighter surrounding and approximating its size) and manually terminate the episode if this mechanism fails.
Figure 5: Comparison of three agents (described in Section 6) on the Donkey simulator. We plot the mean and standard deviation of three different runs for every agent. All agents are able to learn to drive. Pretrained VAE enables slightly faster learning and joint training of the VAE encoder using the critic loss enables better convergence.

We preprocess the images from the camera before feeding it to the agent. We first convert the 120 × 160 image to grayscale as it still contains all the relevant information. We then crop out the top 40 × 160 pixels in the image as it is mostly surroundings that are not relevant to the track. We finally resize the resulting images to 40 × 40 pixels. The latent representations or embeddings of the images are obtained by passing them through the VAE encoder. We concatenate the image embedding with a history of 20 previous controls since the dynamics of the car also depend on the immediate past controls and the policy can learn these dynamics.

The VAE encoder consists of three 3 × 3 convolutional layers and a linear layer to predict the mean and variance parameters of the latent distribution. The first convolutional layer has 16 channels with a stride of 2 and others have 32 channels with a stride of 1. We use a dimension of 20 for the latent representations. The VAE decoder similarly consists of a linear layer and three deconvolutional layers to reconstruct the images from a 20-dimensional embedding. We use the predicted mean as the embedding of the image. The image embedding and the control history are fed into the SAC networks. The policy and value networks are fully connected networks with two hidden layers and 64 hidden units in each layer. We use the ReLU non-linearity in all the networks. We use Adam optimizer with a learning rate of 0.0001 for all our networks and jointly optimize the critic and VAE parameters with a single optimizer. We perform the SAC and VAE updates 600 times by sampling different batches of size 128 from the replay buffer at the end of each episode.

6 Experiments on Donkey Car Simulator

We first evaluate the learning algorithm on the Donkey car simulator. The Donkey car simulator is based on the Unity game platform and is wrapped in an easily accessible OpenAI Gym interface. See Figure 2 for a screenshot of the simulator. The simulator dynamics is discretized so that each environment step roughly corresponds to 0.1 seconds.

In the Donkey car simulator, the task is to learn to drive the Donkey car in randomly generated tracks. The agent has to learn to control the throttle and steering of the car based on image observations from an on-board camera view. The agent receives a reward of 1 for every step that it stays on the road and a penalty of -10 when it drives off the road.

In the experiments on the simulator, we aim to evaluate: 1) the effectiveness of pretraining the state representation learning, and, 2) sample-efficiency and stability of the reinforcement learning algorithm. We consider three different learning agents to evaluate this:
The pretrained VAE is trained using images observations collected using a policy trained to convergence from scratch. We rollout this policy to collect a dataset of 10,000 image observations. We train a VAE on these images until convergence by sampling batches of size 128 and updating the weights with a learning rate of 0.0001.

The results of our experiments on the Donkey car simulator are shown in Figure 5. The maximum cumulative reward that an agent can achieve in the simulator task is 1000. All of the three different agents we consider are able to consistently learn to drive well in the simulator, on randomly generated tracks roughly after driving for just 15 minutes. Agents with a pretrained VAE learns slightly faster in the initial stages of learning. The agent with fixed state representations learn the fastest but fails to converge to a completely stable policy as well as the other agents. We demonstrate that learning from scratch can converge to stable policies that achieve the maximal performance.

Previous works on reinforcement learning in the Donkey car simulator were unsuccessful in stable joint training of SAC with VAE and instead resort to the use of fixed pretrained VAEs for state representations [23]. This is limiting as one requires expert demonstrations to collect a good dataset for pretraining the state representations. Also, the use of fixed representations is brittle since they don’t adapt to learning signals that are important for control. We found truncating the actor gradients to the VAE encoder to be important in achieving stable joint training. We demonstrate that training the VAE encoder jointly with the critic gradients enables it to learn better representations, leading to better control performance.

7 Experiments on Donkey Car Platform

In this section, we perform the same experiments as the simulator on the real-world using the Donkey car platform. We found that the simulator dynamics is much simpler than the real-world. The
simulator dynamics presents no significant resistive forces. The car moves smoothly when the throttle is applied and slowly comes to a stop when no throttle is applied. This makes it very easy to drive in the simulator. In contrast, a low throttle in the real car results in the car not moving at all since the resistive forces are greater than the torque from the motor. When a slightly higher throttle that can provide more torque than the resistive forces is applied, the car will accelerate very quickly. The acceleration of the car is also adversely affected by other factors such as battery voltage and temperature. The real-world dynamics is more challenging with this noisy nonlinear dynamics. It is very difficult for an RL agent to learn to control the throttle without access to a reliable estimate of the speed of the car. In our real-world experiments, we only control the steering and set the throttle based on battery discharge in the beginning of an episode and keep it constant during the episode, such that the car roughly maintains a speed of around 0.5 m/s.

We wrap the remote communication setup with the Donkey platform using the same OpenAI Gym interface as the simulator. An environment step in our remote setup also corresponds to \( \sim 0.1 \) seconds. Each training run is split into training episodes. Each training episode starts from the same position in the track and is terminated when the car drives off the track. Note that terminating an episode when the car drives off the track leads to sparse and noisy rewards. Each training run is started with five episodes of data collection using a random policy. A successful training episode involves the car completing three lap around the track, which corresponds to a maximum cumulative reward of 500. A training run is continued until the agent is able to consistently complete three laps around the track.

We evaluate the same agents described in Section 6 on the Donkey car platform. Similar to the experiments on the simulator, we first pretrain a VAE using 10,000 images collected using a policy trained to convergence from scratch. We use the same network architecture and hyperparameters in both the simulator and real-world experiments in this paper. The results of our experiments on the Donkey car platform are shown in Figure 6. Similar to the simulator, all three agents are able to learn to consistently drive around the track. All agents learn to drive around the track in roughly 6000 steps or approximately 10 minutes of experience \(^1\). In contrast to our experiments on the simulator, we observe that learning from scratch works the best in the real-world. We observe that the use of fixed representations leads to better performance in the early stages of a training run but training from scratch leads to better stable performance as training progresses. This difference is due to the simplicity of the images on the simulator. The image observations from the random tracks generated on the simulator primarily consist of the car, track, and plain surroundings. The image observations from the real-world consist of random objects around the track and the VAE will also learn to represent them. Training the VAE encoder jointly with the critic loss enables it to focus its representation capacity more on the relevant parts of the image.

8 Conclusion

In this paper, we considered the problem of learning to drive small scale RC cars around a track. We propose to use the existing Donkey car platform for low-cost research in autonomous driving. We use a VAE to learn state representations and the SAC algorithm to learn to drive the car based on these state representations. We evaluate the learning algorithm on randomly generated tracks on the Donkey car simulator and on a real-world track with the Donkey car platform. We demonstrate that the learning algorithm is able to consistently learn a stable policy from scratch using sparse and noisy rewards in roughly 10 minutes of driving experience. We release the code for our experiments so that they are easily reproducible on the low-cost Donkey car platform.

Learning to control the throttle of the Donkey car would require access to reliable estimates of the speed of the car. This can be achieved by 1) a rotary encoder used to measure the speed of the motor shaft, 2) an Intel RealSense T265 tracking camera - a small, light and low power SLAM device that can estimate distance and velocity using it’s two fisheye lens sensors and an IMU, and 3) visual odometry algorithms using images from the on-board wide-angle RGB camera. Distance and/or speed estimates could also be used to compute better reward functions for more efficient learning. The sample-efficiency of learning could also be potentially improved using model-based RL algorithms \([24, 25]\), at the cost of more computation.

\(^1\)See https://sites.google.com/view/donkeycar for a supplementary video containing a complete session of training from scratch.
References

[1] S. Thrun, W. Burgard, and D. Fox. *Probabilistic Robotics*. MIT Press, 2005.

[2] M. Bojarski, D. Del Testa, D. Dworakowski, B. Firner, B. Flepp, P. Goyal, L. D. Jackel, M. Monfort, U. Muller, J. Zhang, et al. End to end learning for self-driving cars. *arXiv preprint arXiv:1604.07316*, 2016.

[3] J. Schmittwieser, I. Antonoglou, T. Hubert, K. Simonyan, L. Sifre, S. Schmitt, A. Guez, E. Lockhart, D. Hassabis, T. Graepel, et al. Mastering atari, go, chess and shogi by planning with a learned model. *arXiv preprint arXiv:1911.08265*, 2019.

[4] I. Akkaya, M. Andrychowicz, M. Chociej, M. Litwin, B. McGrew, A. Petron, A. Paino, M. Plappert, G. Powell, R. Ribas, et al. Solving rubik’s cube with a robot hand. *arXiv preprint arXiv:1910.07113*, 2019.

[5] A. W. Senior, R. Evans, J. Jumper, J. Kirkpatrick, L. Sifre, J. Schrittwieser, I. Antonoglou, T. Hubert, K. Simonyan, L. Sifre, S. Schmitt, A. Guez, E. Lockhart, D. Hassabis, T. Graepel, et al. Improved protein structure prediction using potentials from deep learning. *Nature*, 577(7792):706–710, 2020.

[6] A. Kendall, J. Hawke, D. Janz, P. Mazur, D. Reda, J.-M. Allen, V.-D. Lam, A. Bewley, and A. Shah. Learning to drive in a day. In 2019 *International Conference on Robotics and Automation (ICRA)*, pages 8248–8254. IEEE, 2019.

[7] Donkey car. *https://www.donkeycar.com/*. Accessed: 2020-07-27.

[8] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba. OpenAI Gym. *arXiv preprint arXiv:1606.01540*, 2016.

[9] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *International Conference on Machine Learning*, pages 1861–1870, 2018.

[10] T. Haarnoja, A. Zhou, K. Hartikainen, G. Tucker, S. Ha, J. Tan, V. Kumar, H. Zhu, A. Gupta, P. Abbeel, et al. Soft actor-critic algorithms and applications. *arXiv preprint arXiv:1812.05905*, 2018.

[11] T. Haarnoja, S. Ha, A. Zhou, J. Tan, G. Tucker, and S. Levine. Learning to walk via deep reinforcement learning. *arXiv preprint arXiv:1812.11103*, 2018.

[12] A. Singh, L. Yang, K. Hartikainen, C. Finn, and S. Levine. End-to-end robotic reinforcement learning without reward engineering. *Robotics: Science and Systems*, 2019.

[13] S. Ha, P. Xu, Z. Tan, S. Levine, and J. Tan. Learning to walk in the real world with minimal human effort. *arXiv preprint arXiv:2002.08550*, 2020.

[14] D. P. Kingma and M. Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

[15] E. Shelhamer, P. Mahmoudieh, M. Argus, and T. Darrell. Loss is its own reward: Self-supervision for reinforcement learning. *arXiv preprint arXiv:1612.07307*, 2016.

[16] I. Higgins, A. Pal, A. Rusu, L. Matthey, C. Burgess, A. Pritzel, M. Botvinick, C. Blundell, and A. Lerchner. Darla: Improving zero-shot transfer in reinforcement learning. In *International Conference on Machine Learning*, pages 1480–1490, 2017.

[17] A. V. Nair, V. Pong, M. Dalal, S. Bahl, S. Lin, and S. Levine. Visual reinforcement learning with imagined goals. In *Advances in Neural Information Processing Systems*, pages 9191–9200, 2018.

[18] Y. Tassa, Y. Doron, A. Muldal, T. Erez, Y. Li, D. d. L. Casas, D. Budden, A. Abdolmaleki, J. Merel, A. Lefrancq, et al. Deepmind control suite. *arXiv preprint arXiv:1801.00690*, 2018.

[19] D. Yarats, A. Zhang, I. Kostrikov, B. Amos, J. Pineau, and R. Fergus. Improving sample efficiency in model-free reinforcement learning from images. *arXiv preprint arXiv:1910.01741*, 2019.
[20] M. Jaderberg, V. Mnih, W. M. Czarnecki, T. Schaul, J. Z. Leibo, D. Silver, and K. Kavukcuoglu. Reinforcement learning with unsupervised auxiliary tasks. In International Conference on Learning Representations, 2016.

[21] M. Riedmiller, M. Montemerlo, and H. Dahlkamp. Learning to drive a real car in 20 minutes. In 2007 Frontiers in the Convergence of Bioscience and Information Technologies, pages 645–650. IEEE, 2007.

[22] Y. Duan, X. Chen, R. Houthooft, J. Schulman, and P. Abbeel. Benchmarking deep reinforcement learning for continuous control. In International Conference on Machine Learning, pages 1329–1338, 2016.

[23] A. Raffin and R. Sokolkov. Learning to drive smoothly in minutes. https://github.com/araffin/learning-to-drive-in-5-minutes/, 2019.

[24] G. Williams, N. Wagener, B. Goldfain, P. Drews, J. M. Rehg, B. Boots, and E. A. Theodorou. Information theoretic mpc for model-based reinforcement learning. In 2017 IEEE International Conference on Robotics and Automation (ICRA), pages 1714–1721. IEEE, 2017.

[25] D. Hafner, T. Lillicrap, J. Ba, and M. Norouzi. Dream to control: Learning behaviors by latent imagination. In International Conference on Learning Representations, 2020.