Learning Visual Robotic Control Efficiently with Contrastive Pre-training and Data Augmentation

Albert Zhan*1, Ruihan (Philip) Zhao*1, Lerrel Pinto2, Pieter Abbeel1, Michael Laskin1

Abstract—Recent advances in unsupervised representation learning significantly improved the sample efficiency of training reinforcement learning policies in simulated environments. However, similar gains have not yet been seen for real-robot reinforcement learning. In this work, we focus on enabling data-efficient real-robot learning from pixels. We present Contrastive Pre-training and Data Augmentation for Efficient Robotic Learning (CoDER), a method that utilizes data augmentation and unsupervised learning to achieve sample-efficient training of real-robot arm policies from sparse rewards. While contrastive pre-training, data augmentation, demonstrations, and reinforcement learning are alone insufficient for efficient learning, our main contribution is showing that the combination of these disparate techniques results in a simple yet data-efficient method. We show that, given only 10 demonstrations, a single robotic arm can learn sparse-reward manipulation policies from pixels, such as reaching, picking, moving, pulling a large object, flipping a switch, and opening a drawer in just 30 minutes of mean real-world training time. We include videos and code on the project website: https://sites.google.com/view/efficient-robotic-manipulation/home.

I. INTRODUCTION

Recent advances in deep reinforcement learning (RL) have given rise to unprecedented capabilities in autonomous decision making. Notable successes include learning to solve a diverse set of challenging video games [1], [2], [3], mastering complex classical games [4], and learning autonomous robotic control policies in both simulated [5], [6] and real-world settings [7], [8]. In particular, deep RL has been an effective method for learning diverse robotic manipulation policies such as grasping [9] and dexterous in-hand manipulation of objects [10].

However, to date, general purpose RL algorithms have been extremely sample inefficient, which has limited their widespread adoption in the field of robotics. State-of-the-art RL algorithms for discrete [11] and continuous [12] control often require tens of millions of environment interactions to learn effective policies from image input [13], while training the Dota5 agent [2] to perform competitively to human experts required an estimated 180 human-years of game play. Even when the underlying proprioceptive state is accessible, sparse reward robotic manipulation still needs millions of training samples [14], to achieve reliable success rates on fundamental tasks such as reaching, picking, pushing, and placing objects.

1 University of California, Berkeley, 2 New York University {albertzhan,philipzhao}@berkeley.edu * Equal contribution

Fig. 1: CoDER enables robotic agents to learn skills directly from pixels in less than one hour of training. Our setup requires a robotic arm, two cameras, and a joystick to provide 10 demonstrations.

Another common approach to learned robotic control is through imitation learning [15], [16], [17], where a large number of expert demonstrations are collected and the policy is extracted through supervised learning by regressing onto the expert trajectories. However, imitation learning can take up to hundreds or thousands of expert demonstrations [18], [19], [17], which are laborious to collect, and the resulting policies are bounded by the quality of expert demonstrations. It would be more desirable to learn the optimal policy required to solve a particular task autonomously.

In this work, rather than relying on transferring policies from simulation or labor intensive human input through imitation learning or environment engineering, we investigate how pixel-based RL applied to real robots can be made data-efficient. Recent progress in unsupervised representation learning [20], [21] and data augmentation [5], [22] has significantly improved the efficiency of learning with RL in simulated robotic [13] and video game [23] environments. The primary strength of these methods is learning high quality representations from image input either explicitly through unsupervised learning or implicitly via data augmentation.

Building on these advances, we propose Contrastive Pre-training and Data Augmentation for Efficient Robotic Learn-
ing (CoDER), shown in Figure 2. CoDER utilizes off-policy RL with data augmentation along with unsupervised pre-training to learn efficiently with a simple three-staged procedure. First, a small number of (10) demonstrations are collected and stored in a replay buffer. Second, the convolutional encoder weights are initialized with unsupervised contrastive pre-training on the demonstration data. Third, an off-policy RL algorithm is trained with augmented images on both data collected online during training and the initial demonstrations. Our core contribution is the novel combination of contrastive pre-training, online data augmentations, and utilizing a small number of demonstrations that together enable efficient real-robot learning from pixels. In contrast, prior leading algorithms that utilize these components individually are unable to learn efficiently on real robots.

We summarize our key contributions and benefits of the CoDER algorithm: (1) Data-efficiency: As shown in Figure 4, CoDER enables learning optimal policies on 6 diverse manipulation tasks, in 15-50 minutes of total training time for each task. These tasks include reaching, pushing, moving, pulling a large object, flipping a switch and drawer opening, as shown in Figure 3. (2) Real-robot deployment: CoDER trains efficiently on real robotic hardware. (3) Simplicity: CoDER is a combination of existing ideas such as contrastive pre-training, data augmentation, and demonstrations that results in a simple and easy to reproduce algorithm. (4) General & lightweight setup: Our setup requires a robot, one GPU, two RGB cameras, a handful of demonstrations, and a sparse reward function. These requirements are quite lightweight relative to setups that rely on Sim2Real, motion capture, multiple robots, point-cloud estimates, or engineering dense rewards. This work shows how recent advances in contrastive learning and data augmentation can enable efficient real-robot reinforcement learning from pixels.

II. BACKGROUND

Soft Actor Critic: The Soft Actor Critic (SAC) [24] is an off-policy RL algorithm that jointly learns an action-conditioned state value function through Q learning and a stochastic policy by maximizing expected returns. SAC is a state-of-the-art model-free RL algorithm for continuous control from state [24] and, in the presence of data augmentations, from pixels as well [5], [22]. In simulated benchmarks, such as DeepMind control [13], SAC is as data-efficient from pixels as it is from state [5]. For this reason, we utilize it as our base RL algorithm for sparse-reward manipulation in this work. As an actor-critic method, SAC learns an actor policy \( \pi_\theta \) and an ensemble of critics \( Q_{\phi_1} \) and \( Q_{\phi_2} \).

To learn the actor policy, samples are collected stochastically from \( \pi_\theta \) such that \( a_\theta(o, \xi) \sim \tanh(\mu_\theta(o) + \sigma_\theta(o) \odot \xi) \), where \( \xi \sim \mathcal{N}(0, I) \) is a sample from a normalized Gaussian noise vector, and then trained to maximize the expected return as shown in eq. 1.

\[
\mathcal{L}(\theta) = \mathbb{E}_{o \sim p} \left[ Q^*(o, a) - \alpha \log \pi_\theta(a|o) \right]
\] (1)

Simultaneously to learning the policy, SAC also trains the critics \( Q_{\phi_1} \) and \( Q_{\phi_2} \) to minimize the Bellman equation in 2. Here, a transition \( t = (o, a, o', r, d) \) is sampled from the replay buffer \( B \), where \( (o', r) \) are consecutive timestep observations, \( a \) is the action, \( r \) is the reward, and \( d \) is the terminal flag.

\[
\mathcal{L}(\phi, B) = \mathbb{E}_{t \sim B} \left[ (Q_{\phi_1}(o, a) - (r + \gamma(1 - d)Q_{\text{target}}))^2 \right]
\] (2)

The function \( Q_{\text{target}} \) is the target value that the critics are trained to match, defined in 3. The target is the entropy regularized exponential moving average (EMA) of the critic ensemble parameters, which we denote as \( \bar{Q}_\phi \).

\[
Q_{\text{target}} = \left( \min_{i=1,2} Q_{\phi_i}(a', a') - \alpha \log \pi_\theta(a'|a') \right)
\] (3)

where \( (a', a') \) are the consecutive timestep action and observation, and \( \alpha \) is a positive action-entropy coefficient. A non-zero action-entropy term improves exploration – the higher the value of \( \alpha \) the more entropy maximization is prioritized over optimizing the value function.
Fig. 3: The set of real world tasks used in this work, along with their pixel observations. Each column shows initial, intermediate, and completion states of a rollout during evaluation of our optimal policy. The right two images comprise the processed camera image input, which are concatenated and used as the observational input for the RL agent. The sparse reward is only given when the robot completes the task. CoDER is able to solve all 6 tasks within an hour, using only 10 demonstrations.

**Unsupervised Contrastive Pretraining:** Contrastive learning [25], [26], [27], [28], [29], [30], [31] aims to maximize agreement between positive examples in data while minimizing agreement between negative examples. Contrastive methods require the specification of query-key pairs, also known as anchors and positives, which are similar data pairs whose agreement needs to be maximized. Given a query $q$ and a key $k$, we seek to maximize the score $f_{\text{score}}(q, k)$ between them while minimizing them between the query $q$ and negative examples in the dataset $k_-$. The score function is most often represented as an inner product, such as a dot product $f_{\text{score}}(q, k) = q^T k$ [27], [28] or a bilinear product $f_{\text{score}}(q, k) = q^T W k$ [26], [31], while other Euclidean metrics are also available [32], [33]. Modern contrastive approaches [29], [30], [31], [20] employ the InfoNCE loss [26], which is described in 4 and can also be interpreted as a multi-class cross entropy classification loss with $K$ classes.

$$
\mathcal{L}_q = \log \frac{\exp(q^T W k)}{\exp(\sum_{i=0}^{K} \exp(q^T W k_i))}
$$

(4)

In the computer vision setting, a simple and natural choice of query-key specification is to define queries and keys as two data augmentations of the same image. This approach, called instance discrimination, is used in most of the state-of-the-art representation learning methods for static images [29], [30] as well as RL from pixels [20]. In the minibatch setting, we also employ in this work, the InfoNCE loss is computed by sampling $K = \{x_1, \ldots, x_K\}$ images from the dataset, generating queries $Q = \{q_1, \ldots, q_K\}$ and keys $K = \{k_1, \ldots, k_K\}$ with stochastic data augmentations $q_i, k_i = \text{aug}(x_i)$, and using each augmented datapoint $x_i$ as positives while the rest of the images are negatives.

**III. Method**

Our proposed method, shown in Figure 2, combines demonstrations, unsupervised pre-training, and off-policy model-free RL with data augmentation into one holistic framework. CoDER has three distinct steps — (i) minimal collection of demonstrations (ii) encoder initialization with unsupervised pre-training and (iii) online policy learning through RL with augmented data — which we describe in detail below.

**Minimal Collection of Demonstrations:** We initialize the replay buffer with a small number of expert demonstrations (we found 10 to be sufficient) for each task. Demonstrations are collected with a joystick controller, shown in Figure 1. Our goal is to minimize the total time required to acquire a skill for an RL agent, including both policy training as well as time required to collect demonstrations. While collecting a larger number of demonstrations certainly improves training speed, we find 10 demonstrations is already sufficient to learn skills quickly (see Fig. 6 Left). For real world experiments, collecting 10 expert demonstrations can be done within 10 minutes which includes the time needed to reset the environment after every demonstration.

**Unsupervised Encoder Pre-training:** After initializing the replay buffer with 10 demonstrations, we pre-train the convolutional encoder with instance-based contrastive learning, using stochastic random crop [20] to generate query-key pairs. The key encoder is an exponentially moving average of the query encoder [30], and the similarity measure between query-key pairs is the bi-linear inner product [26] shown in 4. Note that the bi-linear inner product is only used to pre-train the encoder. After pre-training, the weight matrix in the bi-linear measure is discarded.

**Reinforcement Learning with Augmented Data:** After pre-training the convolutional encoder on offline demonstration data, we train a SAC [24] agent with data augmentation [5] as the robot interacts with the environment. Since the
replay buffer was initialized with demonstrations and SAC is an off-policy RL algorithm, during each minibatch update the agent receives a mix of demonstration observations and observations collected during training when performing gradient updates. The image augmentation used during training is random crop – the same augmentation used during contrastive pre-training.

IV. EXPERIMENTAL EVALUATION

A. Experimental Setup

**Real robot**: We use the xArm [34] robot for all real-world experiments. The end effector, a parallel two-jaw gripper, is position controlled with three degrees of freedom. At each step, the robot takes in an action containing the end effector and gripper aperture displacement.

**Operation space**: The range of motion of the gripper is confined to a 25 cm-high imaginary box above the manipulation surface. For majority of the tasks, objects are contained in a plastic tray approximately 40 × 34 cm in size measured at its bottom. Sponge padding was placed below the tray to absorb minor collisions between the gripper and the objects.

**Input**: We use two RGB cameras, one positioned over the shoulder for maximal view of the arm, and the other located within the gripper to provide a local object-level view. The over-the-shoulder camera is an Intel Realsense D415, with native resolution of 1280 × 720, and only the RGB frames are utilized during both training and testing. Inside the gripper, we use an Arducam 8MP camera module configured to 640 × 480 in resolution. Image frames from both cameras are cropped and down-sampled to 100 × 100 pixels for use in our training algorithm.

**Demonstrations**: Using an Xbox controller [35], we teleoperate the robot by supplying the end effector and gripper aperture displacement. Collecting demonstrations for each task requires less than 10 minutes. This is a very loose upper bound, which includes physically resetting the environment, and also accounts for possible human error and inefficiency during the demonstration collection phase.

B. Environments and Baselines

**Environments**: We evaluate CoDER on six real-robotic manipulation tasks - reaching an object, picking up a block, moving a block to a target destination, pulling a large deformable object, flipping a switch, and opening a drawer. The block manipulation tasks (reach, pickup, move) are real-world adaptations of tasks from the OpenAI Gym Fetch suite [36]. We utilize these three OpenAI gym environments for simulated environment experiments. Since our method uses demonstrations, we include pull, which has been used in prior work on imitation learning [37], [38]. Flipping a switch is included as it demands precision, while drawer opening is a common task in existing simulated robotic benchmarks [39].

**Baselines**: We compare CoDER to RAD [5], a leading supervised RL algorithm in simulated environments, and behavior cloning for our main results in Fig. 5. In the ablations section, we investigate each individual component of CoDER. We investigate the contribution of each component of the CoDER algorithm by removing one component - demonstrations, contrastive pre-training, or data augmentation - while keeping others fixed.

C. Results

The main results of our investigation, including the time required to train an optimal policy as well the first successful task completion, are shown in Figure 5 and Table I. We summarize the key findings below:

(i) On average, CoDER enables a single robotic arm to learn optimal policies across all 6 tasks tested within 30 minutes of training time with a range of 15-50 minutes, which corresponds to 20-80 episodes of training. (see Figure 4 and Table I).

(ii) When evaluated on 3 simulated and 3 real-robot tasks, CoDER substantially outperforms RAD and behavior cloning baselines (see Figure 5).

(iii) The time to first successful task completion is on average 11 minutes with a range of 3-33 minutes. The final
policies achieve an average success rate of 96% with a range of 86-100% across the tasks tested, suggesting that they have converged to near-optimal solutions to the tasks.

(iv) Collecting demonstrations and contrastive pre-training does not introduce significant overhead in terms of time. Collecting 10 expert demonstrations with a joystick requires 10 minutes of human operation. Contrastive pre-training completes within one minute on a single NVIDIA 2080Ti GPU.

(v) CoDER solves all 6 tasks using the same hyperparameters and without altering the camera setup, which demonstrates the ease of use and generality of the framework.

Altogether, an RL agent trained with CoDER is able to learn optimal policies for the 6 tasks extremely efficiently. CoDER is a reinforcement learning method that is able to solve a diverse set of sparse-reward robotic manipulation tasks directly from pixels in less than one hour.

D. Ablations

In this section, we investigate how the three core components of CoDER – demonstrations, contrastive pre-training, and data augmentation – contribute to the overall efficiency of the framework through ablations in simulated environments, shown in Figure 7.

**How many demonstrations are needed?**

While sparse rewards are simpler to define, they pose an exploration challenge since the robot is unlikely to randomly stumble on a reward state. We address this issue by providing demonstrations to the RL agent. We ablate the number of demonstrations required to learn efficiently on the simulated pick and place task in Figure 6. We find that while the agent fails entirely with zero demonstrations, it is able to start learning the task with just one demonstration. While more demonstrations improve learning efficiency and reduce the variance of the policy, ten demonstrations suffice to learn quickly. We then evaluate the effectiveness of the 10 demonstrations by comparing our method to training behavior cloning. As shown in Figure 5, the 10 demonstrations are not enough to learn an effective policy.

**How important is unsupervised contrastive pre-training?**

We next study the role of contrastive pre-training in CoDER. We ablate our method with and without contrastive pre-training on the real world pickup and move task, shown in Figure 6, where we compare with 0 and with 1600 iterations of pre-training to initialize the encoder. With 1600 contrastive

![Fig. 5: Baseline Comparisons. Shown are normalized rewards of the agent at the end of training for the simulated as well as the real robot results, as well as standard error. Reward is normalized by the maximum possible reward for all environments. While CoDER is able to learn all the tasks, the baseline RL agent (RAD) is able to learn only one sparse reward task without demonstrations. Conversely, with access to only 10 demonstrations, behavior cloning is unable to learn in the more difficult environments, and only succeeds on the simpler tasks (FetchReach, Light Switch). CoDER and RAD are trained for 200k environment steps in simulated tasks, and until convergence for real world tasks (30 episodes for Switch and Pickup, 60 episodes for Move). BC is trained over the dataset for 200 epochs for both simulated and real world tasks. Simulated tasks are evaluated over 100 episodes, while real world tasks are evaluated over 30 episodes.

| Tasks           | Reach | Pickup | Move | Pull | Light Switch | Drawer Open |
|-----------------|-------|--------|------|------|--------------|-------------|
| # Successes (/30) | 30    | 30     | 26   | 28   | 30           | 30          |
| Success Rate (%) | 100   | 100    | 86   | 93   | 100          | 100         |

| Tasks          | CoDER (ours) | RAD | BC |
|----------------|--------------|-----|----|
| FetchReach     | 1.0          | 0.8 | 0.4|
| FetchPickAndPlace | 0.6          | 0.5 | 0.2|
| FetchPush      | 0.9          | 0.7 | 0.5|
| Switch         | 1.0          | 0.8 | 0.4|
| Pickup         | 0.9          | 0.7 | 0.5|
| Move           | 0.9          | 0.7 | 0.5|
Fig. 6: Left: We ablate the number of demonstrations required by CoDER, and find that although the agent fails to learn with zero demonstrations, it can learn the PickAndPlace task efficiently using only 10 demonstrations. Center: We compare the performance of the move task with and without the use of pre-training on the real xArm robot. The plotted episode returns at convergence show that the contrastive pre-training substantially boosts performance. Right: Using data augmentation, the agent achieves successful performance. Using non-augmented observations, the agent fails to learn the task.

![Graphs showing the effect of demonstrations and pre-training on task performance.](image)

V. RELATED WORK

Imitation Learning: Imitation learning is a framework for learning autonomous skills from demonstrations. One of the simplest and perhaps most widely used forms of imitation learning is behavior cloning (BC) where an agent learns a skill by regressing onto demonstration data. BC has been successfully applied across diverse modalities including video games [40], autonomous navigation [41], [42], autonomous aviation [43], locomotion [44], [45], and manipulation [15], [16], [37]. Other imitation learning approaches include Dataset Aggregation [46], and Inverse Reinforcement Learning [47], [48]. A general limitation of imitation learning approaches is the requirement for a large number of demonstrations for each task [49]. Although recent advancements have shown that imitation learning can learn with a much more modest amount of demonstrations [15], [37], [38], CoDER can learn in the same number of episodes, of which the majority are spent with reinforcement learning.

Reinforcement Learning: Reinforcement Learning (RL) has been a promising approach for robotic manipulation due to its ability to learn skills autonomously. Recently, deep RL methods excelled at playing video games from pixels [1], [2] as well as learning robotic manipulation policies from visual input [7], [50], [24]. However, widespread adoption of RL in real-world robotics has been bottle-necked due to the data-inefficiency of the method, among other factors such as safety. Though there exist prior frameworks for efficient position controlled robotic manipulation [51], [52], they still require hours of training while providing additional information such as a dense reward function, or heavy computation along with depth information. CoDER is most closely related to other methods that use RL with demonstrations. Prior methods [53], [54], [55] solve robotic manipulation tasks from coordinate state input, rather than image input, by initializing the replay buffer of an RL algorithm with demonstrations to overcome the exploration problem in the sparse reward setting. Recent advances in vision-based imitation learning is also able to learn with limited amount of demonstrations [17], [19], [18], however, the learned policy distribution is still limited by the distribution provided by the experts.

Data Augmentation: Image augmentation refers to stochastically altering images through transformations such as cropping, rotating, or color-jittering. It is widely used in computer vision architectures including seminal works such as LeNet [56] and AlexNet [57]. Data augmentation has played a crucial role in unsupervised representation learning in computer vision [31], [30], [29], while other works investigated automatic generation of data augmentation strategies [58]. Data augmentation has also been utilized...
in prior real robot RL methods [8]; however, the extent of its significance for efficient training was not fully understood until recent works [20], [5], [22], which showed that carefully implemented data augmentation makes RL policies from pixels as efficient as those from coordinate state. Finally, data augmentation has also been shown to improve performance in imitation learning [16]. In this work, data augmentation comprises one of three components of a general framework for efficient learning.

Unsupervised Representation Learning: The goal of unsupervised representation learning is to extract representations of high-dimensional unlabeled data that can then be used to learn downstream tasks efficiently. Most relevant to our work is contrastive learning, which is a framework for learning effective representations that satisfy similarity constraints between a pair of points in dataset. In contrastive learning, latent embeddings are learned by minimizing the latent distance between similar data points and maximizing them between dissimilar ones. Recently, a number of contrastive learning methods [31], [28], [29] have achieved state-of-the-art label-efficient training in computer vision. A number of recent investigations in robotics have leveraged contrastive losses to learn viewpoint invariant representations from videos [59], and learn object representations [60]. In this work, we focus on instance-based contrastive learning [27] similar to how it is used in vision [30], [29] and RL on simulated benchmarks [20], [21].

VI. CONCLUSION AND LIMITATIONS

Although CoDER enables data-efficient deployment of RL onto real robots, the method also has a number of limitations. First, like most RL algorithms, CoDER may require assistance for resets, and CoDER policies can only solve the tasks that they were trained on and while they may display some degree of generalization to small changes such as object shape or perturbations, we do not expect CoDER policies to generalize to qualitatively different tasks that were unseen during training. Second, while the tasks considered in this paper are standard robotics evaluation tasks, they all have relatively short horizons. Since CoDER relies on a sparse reward signal to learn, we do not expect this framework to succeed in long-horizon sparse reward tasks, where random interaction with the reward is unlikely. Finally, we expect the performance of CoDER to degrade if the visual conditions of the scene change substantially, which is likely in non-lab settings with frequent background distractors and lighting changes. Rather than addressing generalization to new tasks and visual settings or long-horizon settings, this paper focuses on the data-efficiency problem of training RL policies on real robots. We believe that data-efficient generalization and long-horizon problem solving are important open problem in robot learning that we leave for future work.

VII. ACKNOWLEDGEMENTS

We gratefully acknowledge support from Open Philanthropy, Darpa LwLL, Berkeley Deep Drive and Amazon Web Services. We would also like to thank the reviewers for detailed feedback on our submission.

REFERENCES

[1] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski et al., “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, p. 529, 2015.
[2] C. Berner, G. Brockman, B. Chan, V. Cheung, P. Debiak, C. Dennison, D. Farhi, Q. Fischer, S. Hashme, C. Hesse et al., “Dota 2 with large scale deep reinforcement learning,” arXiv preprint arXiv:1912.06680, 2019.
[3] A. P. Badia, B. Piot, S. Kapturovska, P. Sprechmann, A. Vittitsky, D. Guo, and C. Blundell, “Agent57: Outperforming the atari human benchmark,” in International Conference on Machine Learning, 2020.
[4] J. Schrittwieser, 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:1911.02659, 2019.
[5] M. Laskin, K. Lee, A. Stooke, L. Pinto, P. Abbeel, and A. Srivivas, “Reinforcement learning with augmented data,” arXiv preprint arXiv:2004.14990, 2020.
[6] D. Hafner, T. Lillicrap, J. Ba, and M. Norouzi, “Dream to control: Learning behaviors by latent imagination,” in International Conference on Learning Representations, 2020.
[7] S. Levine, C. Finn, T. Darrell, and P. Abbeel, “http://arxiv.org/abs/1504.00702End-to-End Training of Deep Visuomotor Policies,” CoRR, vol. abs/1504.00702, 2015.
[8] D. Kalashnikov, A. Irpan, P. Pastor, J. Ibarz, A. Herzog, E. Jang, D. Quillen, E. Holly, M. Kalakrishnan, V. Vanhoucke et al., “Qt-opt: Scalable deep reinforcement learning for vision-based robotic manipulation,” arXiv preprint arXiv:1806.10293, 2018.
[9] J. Mahler, F. T. Pokorny, B. Hou, M. Roderick, M. Laskey, M. Aubry, K. Kohlhoff, T. Kröger, J. Kuffner, and K. Goldberg, “Dex-net 1.0: A cloud-based network of 3d objects for robust grasp planning using a multi-armed bandit model with correlated rewards,” in ICRA, 2016.
[10] M. Andrychowicz, B. Baker, M. Chociej, R. Jozefowicz, B. Mc-Grew, J. Pachocki, A. Petron, M. Plappert, G. Powell, A. Ray et al., “Learning dexterous in-hand manipulation,” arXiv preprint arXiv:1808.00177, 2018.
[11] M. Hessel, J. Modayil, H. van Hasselt, T. Schaul, G. Ostrovski, W. Dabney, D. Horgan, B. Piot, M. Azar, and D. Silver, “Rainbow: Combining improvements in deep reinforcement learning,” 2017.
[12] T. P. Lillicrap, J. J. Hunt, A. Pritzel, N. Heess, T. Erez, Y. Tassa, D. Silver, and D. Wierstra, “Continuous control with deep reinforce-

ment learning,” arXiv preprint arXiv:1509.02971, 2015.
[13] Y. Tassa, Y. Doron, A. Muldal, T. Erez, Y. Li, D. d. L. Casas, D. Budden, A. Abdolmaleki, J. Merel, A. Lefracz et al., “Deepmind control suite,” arXiv preprint arXiv:1801.00690, 2018.
[14] M. Andrychowicz, P. Wolski, A. Ray, J. Schneider, R. Fong, P. Welin-der, B. McGrew, I. Tolkin, O. Pieter Abbeel, and W. Zaremba, “Hindsight experience replay,” in NeurIPS, 2017.
[15] T. Zhang, Z. McCarthy, O. Jow, D. Lee, K. Goldberg, and P. Abbeel, “Deep imitation learning for complex manipulation tasks from virtual reality teleoperation,” 2018 IEEE International Conference on Robotics and Automation (ICRA), pp. 1–8, 2018.
[16] S. Young, D. Gandhi, S. Tulsiani, A. Gupta, P. Abbeel, and L. Pinto, “http://arxiv.org/abs/2008.04899 Visual Imitation Made Easy,” CoRR, vol. abs/2008.04899, 2020.
[17] P. Florence, C. Lynch, A. Zeng, O. A. Ramirez, A. Wahid, L. Downs, A. Wong, J. Lee, I. Mordatch, and J. Tompson, “Implicit behavioral cloning,” in Conference on Robot Learning. PMLR, 2022, pp. 158–168.
[18] A. Zeng, P. Florence, J. Tompson, S. Welker, J. Chien, M. Attarian, T. Armstrong, I. Krisan, D. Duong, V. Sindhwani et al., “Transporter networks: Rearranging the visual world for robotic manipulation,” arXiv preprint arXiv:2010.14406, 2020.
[19] P. Florence, L. Manuelli, and R. Tedrake, “Self-supervised correspondence in visuomotor policy learning,” IEEE Robotics and Automation Letters, vol. 5, no. 2, pp. 492–499, 2019.
[20] M. Laskin, A. Srivivas, and P. Abbeel, “Curl: Contrastive unsupervised representations for reinforcement learning,” in International Conference on Machine Learning, 2020.
