Multi-Goal Reinforcement Learning: Challenging Robotics Environments and Request for Research

Matthias Plappert, Marcin Andrychowicz, Alex Ray, Bob McGrew, Bowen Baker, Glenn Powell, Jonas Schneider, Josh Tobin, Maciek Chociej, Peter Welinder, Vikash Kumar, and Wojciech Zaremba
OpenAI

Correspondence to {matthias, marcin}@openai.com

Abstract

The purpose of this technical report is two-fold. First of all, it introduces a suite of challenging continuous control tasks (integrated with OpenAI Gym) based on currently existing robotics hardware. The tasks include pushing, sliding and pick & place with a Fetch robotic arm as well as in-hand object manipulation with a Shadow Dexterous Hand. All tasks have sparse binary rewards and follow a Multi-Goal Reinforcement Learning (RL) framework in which an agent is told what to do using an additional input.

The second part of the paper presents a set of concrete research ideas for improving RL algorithms, most of which are related to Multi-Goal RL and Hindsight Experience Replay.

1 Environments

All environments are released as part of *OpenAI Gym*[1] (Brockman et al., 2016) and use the *MuJoCo* (Todorov et al., 2012) physics engine for fast and accurate simulation. A video presenting the new environments can be found at `https://www.youtube.com/watch?v=8Np3eC_PTFo`.

1.1 Fetch environments

The Fetch environments are based on the 7-DoF Fetch robotics arm,[2] which has a two-fingered parallel gripper. They are very similar to the tasks used in Andrychowicz et al. (2017) but we have added an additional *reaching* task and the *pick & place* task is a bit different.[3]

In all Fetch tasks, the goal is 3-dimensional and describes the desired position of the object (or the end-effector for reaching). Rewards are sparse and binary: The agent obtains a reward of 0 if the object is at the target location (within a tolerance of 5 cm) and -1 otherwise. Actions are 4-dimensional: 3 dimensions specify the desired gripper movement in Cartesian coordinates and the last dimension controls opening and closing of the gripper. We apply the same action in 20 subsequent simulator steps (with $\Delta t = 0.002$ each) before returning control to the agent, i.e. the agent's action frequency is $f = 25$ Hz. Observations include the Cartesian position of the gripper, its linear velocity as well as the position and linear velocity of the robot's gripper. If an object is present, we also include the object's Cartesian position and rotation using Euler angles, its linear and angular velocities, as well as its position and linear velocities relative to gripper.

[1] `https://github.com/openai/gym`
[2] `http://fetchrobotics.com/`
[3] In Andrychowicz et al. (2017) training on this task relied on starting some of the training episodes from a state in which the box is already grasped. This is not necessary for successful training if the target position of the box is sometimes in the air and sometimes on the table and we do not use this technique anymore.

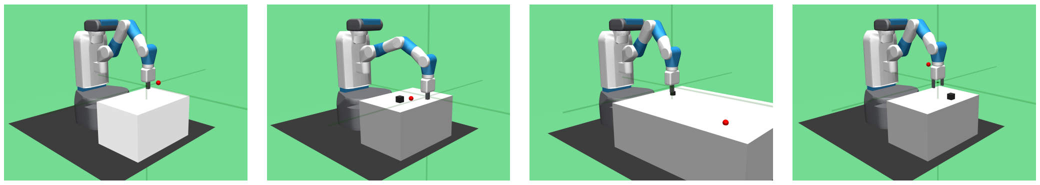


Figure 1: The four proposed Fetch environments: `FetchReach`, `FetchPush`, `FetchSlide`, and `FetchPickAndPlace`.

Reaching (`FetchReach`) The task is to move the gripper to a target position. This task is very easy to learn and is therefore a suitable benchmark to ensure that a new idea works at all.[4]

Pushing (`FetchPush`) A box is placed on a table in front of the robot and the task is to move it to a target location on the table. The robot fingers are locked to prevent grasping. The learned behavior is usually a mixture of pushing and rolling.

Sliding (`FetchSlide`) A puck is placed on a long slippery table and the target position is outside of the robot's reach so that it has to hit the puck with such a force that it slides and then stops at the target location due to friction.

Pick & Place (`FetchPickAndPlace`) The task is to grasp a box and move it to the target location which may be located on the table surface or in the air above it.

1.2 Hand environments

These environments are based on the Shadow Dexterous Hand,[5] which is an anthropomorphic robotic hand with 24 degrees of freedom. Of those 24 joints, 20 can be can be controlled independently whereas the remaining ones are coupled joints.

In all hand tasks, rewards are sparse and binary: The agent obtains a reward of 0 if the goal has been achieved (within some task-specific tolerance) and -1 otherwise. Actions are 20-dimensional: We use absolute position control for all non-coupled joints of the hand. We apply the same action in 20 subsequent simulator steps (with $\Delta t = 0.002$ each) before returning control to the agent, i.e. the agent's action frequency is $f = 25$ Hz. Observations include the 24 positions and velocities of the robot's joints. In case of an object that is being manipulated, we also include its Cartesian position and rotation represented by a quaternion (hence 7-dimensional) as well as its linear and angular velocities. In the reaching task, we include the Cartesian position of all 5 fingertips.

Reaching (`HandReach`) A simple task in which the goal is 15-dimensional and contains the target Cartesian position of each fingertip of the hand. Similarly to the `FetchReach` task, this task is relatively easy to learn. A goal is considered achieved if the mean distance between fingertips and their desired position is less than 1 cm.

Block manipulation (`HandManipulateBlock`) In the block manipulation task, a block is placed on the palm of the hand. The task is to then manipulate the block such that a target pose is achieved. The goal is 7-dimensional and includes the target position (in Cartesian coordinates) and target rotation (in quaternions). We include multiple variants with increasing levels of difficulty:

- `HandManipulateBlockRotateZ` Random target rotation around the z axis of the block. No target position.
- `HandManipulateBlockRotateParallel` Random target rotation around the z axis of the block and axis-aligned target rotations for the x and y axes. No target position.
- `HandManipulateBlockRotateXYZ` Random target rotation for all axes of the block. No target position.

[4]That being said, we have found that is so easy that even partially broken implementations sometimes learn successful policies, so no conclusions should be drawn from this task alone.

[5]https://www.shadowrobot.com/products/dexterous-hand/

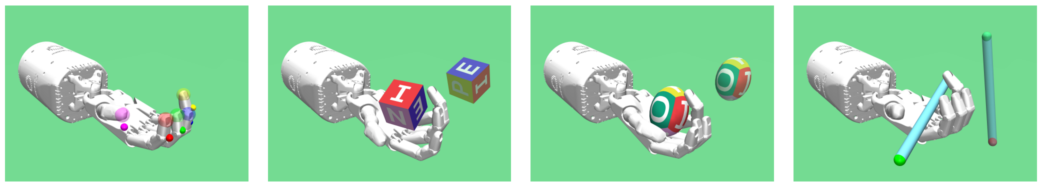


Figure 2: The four proposed Shadow Dexterous Hand environments: `HandReach`, `HandManipulateBlock`, `HandManipulateEgg`, and `HandManipulatePen`.

- `HandManipulateBlockFull` Random target rotation for all axes of the block. Random target position.

A goal is considered achieved if the distance between the block's position and its desired position is less than 1 cm (applicable only in the `Full` variant) and the difference in rotation is less than 0.1 rad.

Egg manipulation (`HandManipulateEgg`) The objective here is similar to the block task but instead of a block an egg-shaped object is used. We find that the object geometry makes a significant differences in how hard the problem is and the egg is probably the easiest object. The goal is again 7-dimensional and includes the target position (in Cartesian coordinates) and target rotation (in quaternions). We include multiple variants with increasing levels of difficulty:

- `HandManipulateEggRotate` Random target rotation for all axes of the egg. No target position.
- `HandManipulateEggFull` Random target rotation for all axes of the egg. Random target position.

A goal is considered achieved if the distance between the egg's position and its desired position is less than 1 cm (applicable only in the `Full` variant) and the difference in rotation is less than 0.1 rad.

Pen manipulation (`HandManipulatePen`) Another manipulation, this time using a pen instead of a block or an egg. Grasping the pen is quite hard since it easily falls off the hand and can easily collide and get stuck between other fingers. The goal is 7-dimensional and includes the target position (in Cartesian coordinates) and target rotation (in quaternions). We include multiple variants with increasing levels of difficulty:

- `HandManipulatePenRotate` Random target rotation x and y axes of the pen and no target rotation around the z axis. No target position.
- `HandManipulatePenFull` Random target rotation x and y axes of the pen and no target rotation around the z axis. Random target position.

A goal is considered achieved if the distance between the pen's position and its desired position is less than 5 cm (applicable only in the `Full` variant) and the difference in rotation, ignoring the z axis,[6] is less than 0.1 rad.

1.3 Multi-goal environment interface

All environments use *goals* that describe the desired outcome of a task. For example, in the `FetchReach` task, the desired target position is described by a 3-dimensional goal. While our environments are fully compatible with the OpenAI Gym API, we slightly extend upon it to support this new type of environment. All environments extend the newly introduced `gym.GoalEnv`.

Goal-aware observation space First, it enforces a constraint on the observation space. More concretely, it requires that the observation space is of type `gym.spaces.Dict` space, with at least the following three keys:

- `observation`: The actual observation of the environment, For example robot state and position of objects.

[6]The z axis of the pen is parallel to its body and goes through its tip to its opposite end.

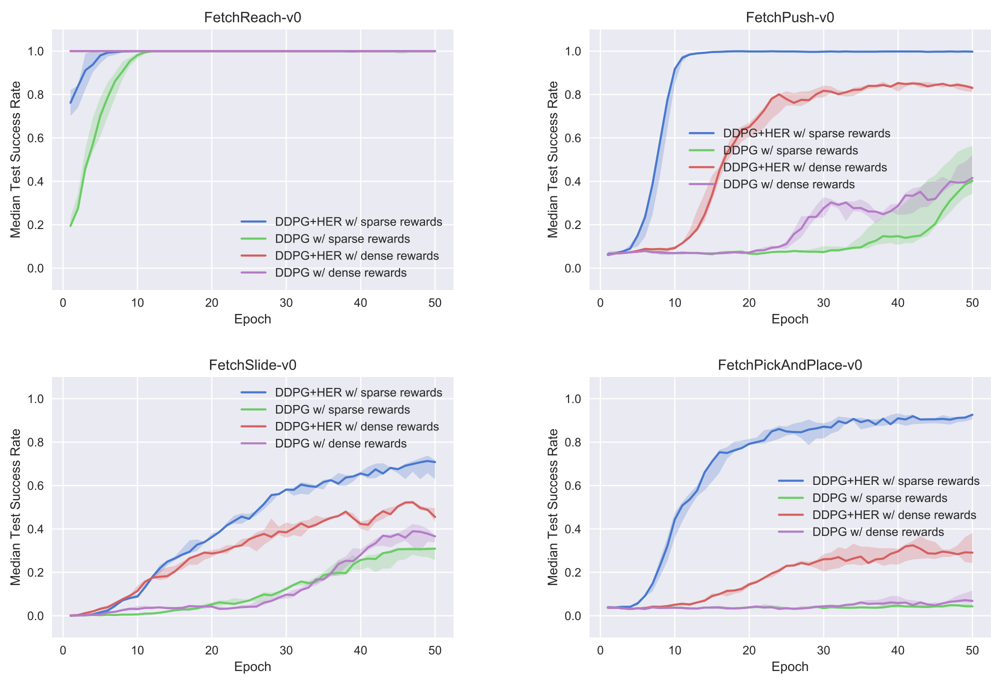


Figure 3: Median test success rate (line) with interquartile range (shaded area) for all four Fetch environments.

- `desired_goal`: The goal that the agent has to achieve. In case of `FetchReach`, this would be the 3-dimensional target position.
- `achieved_goal`: The goal that the agent has currently achieved instead. In case of `FetchReach`, this is the position of the robots end effector. Ideally, this would be the same as `desired_goal` as quickly as possible.

Exposed reward function Second, we expose the reward function in a way that allows for re-computing the reward with different goals. This is a necessary requirement for HER-style algorithms which substitute goals. A detailed example is available in Appendix A

Compatibility with standard RL algorithms Since OpenAI Gym is commonly supported in most RL algorithm frameworks and tools like OpenAI Baselines (Dhariwal et al., 2017), we include a simple wrapper that converts the new dictionary-based goal observation space into a more common array representation. A detailed example is available in Appendix A.

1.4 Benchmark results

We evaluate the performance of DDPG with and without Hindsight Experience Replay (HER, Andrychowicz et al. (2017)) on all environments with all its variants. We compare the following four configurations:

- DDPG+HER with sparse rewards
- DDPG+HER with dense rewards
- DDPG with sparse rewards
- DDPG with dense rewards

Detailed hyperparameters can be found in Appendix B.

For all environments, we train on a single machine with 19 CPU cores. Each core generates experience using two parallel rollouts and uses MPI for synchronization. For `FetchReach`, `FetchPush`, `FetchSlide`, `FetchPickAndPlace`, and `HandReach`, we train for 50 epochs (one epoch consists of $19 \cdot 2 \cdot 50 = 1\,900$ full episodes), which amounts to a total of $4.75 \cdot 10^6$ timesteps. For the remaining

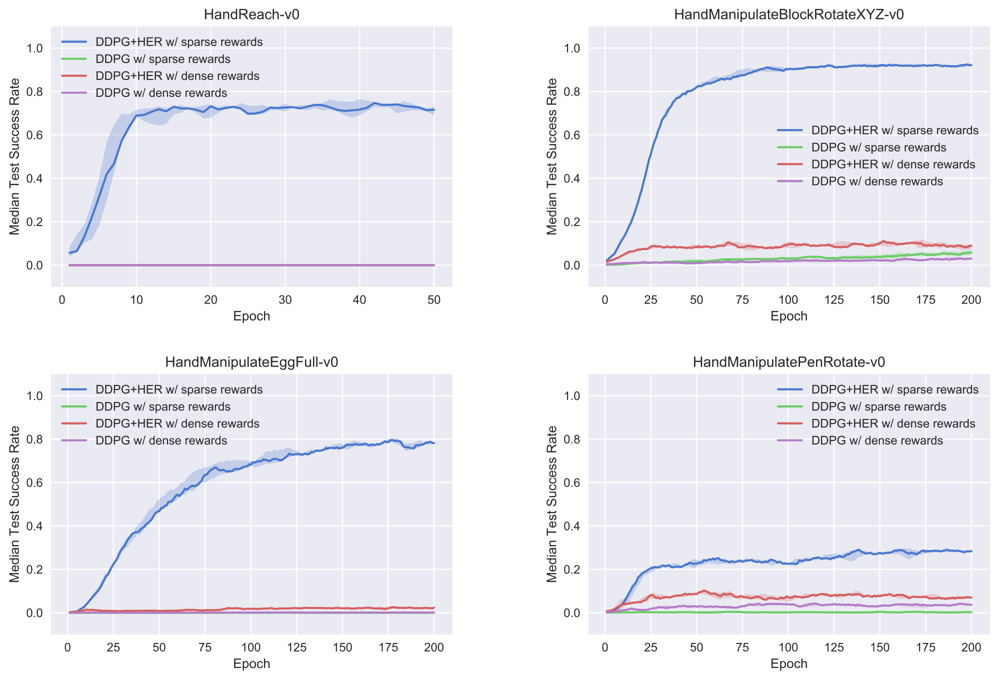


Figure 4: Median test success rate (line) with interquartile range (shaded area) for all four Fetch environments.

environments, we train for 200 epochs, which amounts to a total of $38 \cdot 10^6$ timesteps. We evaluate the performance after each epoch by performing 10 deterministic test rollouts per MPI worker and then compute the test success rate by averaging across rollouts and MPI workers. Our implementation is available as part of OpenAI Baselines[7] (Dhariwal et al., 2017). In all cases, we repeat an experiment with 5 different random seeds and report results by computing the median test success rate as well as the interquartile range.

Figure 3 depicts the median test success rate for all four Fetch environments. `FetchReach` is clearly a very simple environment and can easily be solved by all four configurations. On the remaining environments, DDPG+HER clearly outperforms all other configurations. Interestingly, DDPG+HER performs best if the reward structure is sparse but is also able to successfully learn from dense rewards. For vanilla DDPG, it is typically easier to learn from dense rewards with sparse rewards being more challenging.

Figure 4 depicts the median test success rate for all four hand environments. Similar to the Fetch environments, DDPG+HER significantly outperforms the DDPG baseline. In fact, the baseline often is not able to learn the problem at all. Similar to before, the sparse reward structure works significantly better than the dense reward when using HER. HER is able to learn partly successful policies on all environments but especially `HandManipulatePen` is especially challenging and we are not able to fully solve it. Note that we do not depict results for all variants of the four environments in this figure. A complete set of plots for all environments and their variants can be found in Appendix C.

We believe the reason why DDPG+HER typically performs better with sparse rewards is mainly due to the following two reasons:

- Learning the critic is much simpler for sparse rewards. In the dense case, the critic has to approximate a highly non-linear function that includes the Euclidean distance between positions and the difference between two quaternions for rotations. On the other hand, learning the sparse return is much simpler since the critic only has to differentiate between successful and failed states.

[7] `https://github.com/openai/baselines`

- A dense reward biases the policy towards a specific strategy. For instance, it may be beneficial to first grasp an object properly and then start rotating it towards the desired goal. The dense reward however encourages the policy to chose a strategy that achieves the desired goal directly.

2 Request for Research

Deciding which problem is worth working on is probably the hardest part of doing research. Below we present a set of research problems which we believe can lead to widely-applicable RL improvements. For each problem we propose at least one potential solution but solving many of them will require inventing new ideas. To make tracking the progress of work on these ideas easier, we would like to ask authors to cite this report when publishing related research.

Automatic hindsight goals generation In Andrychowicz et al. (2017) the goals used for HER were generated using a hand-crafted heuristic, e.g. replaying with a goal which was achieved at a random future timestep in the episode. Instead, we could learn which goals are most valuable for replay. They could be chosen from the goals achieved or seen during training or generated by a separate neural network given a transition as input. The biggest question is how to judge which goals are most valuable for replay. One option would be to train the generator to *maximize* the Bellman error. This bears a lot of similarity to Prioritized Experience Replay (Schaul et al., 2015b) and we expect that some techniques from this paper may be useful here.

Unbiased HER HER changes the joint distribution of replayed (state, action, next_state, goal) tuples in an unprincipled way. This could, in theory, make training impossible in extremely stochastic environment albeit we have not noticed this in practice. Consider an environment in which there is a special action which takes the agent to a random state and the episode ends after that. Such an action would seem to be perfect in hindsight if we replay with the goal achieved by the agent in the future. How to avoid this problem? One potential approach would be to use importance sampling to cancel the sampling bias but this would probably lead to prohibitively high variance of the gradient.

HER+HRL Hierarchical Actor-Critic (Levy et al., 2017) showed some promising results in applying HER in Hierarchical RL setup. One possible extension of this work would be to replace in hindsight not only goals, but also higher-level actions, e.g. if the higher level asked the lower level to reach state A, but some other state B was reached, we could replay this episode replacing the higher-level action with B. This could allow the higher level to learn even when the lower level policy is very bad but is not very principled and could make training unstable.

Richer value functions UVFA (Schaul et al., 2015a) extended value functions to multiple goals, while TDM (Pong et al., 2018) extended them to different time horizons. Both of these innovations can make training easier, despite the fact that the learned function is more complicated. What else could we fed to the value function to improve the sample-efficiency? How about discount factor or success threshold for binary rewards?

Faster information propagation Most state-of-the-art off-policy RL algorithms use target networks to stabilize training (e.g. DQN (Mnih et al., 2015) or DDPG (Lillicrap et al., 2015)). This, however, comes at a price of limiting the maximum learning speed of the algorithm as each target network update sends the information about returns only one step backward in time (if one-step bootstrapping is used). We noticed that the learning speed of DDPG+HER in the early stages of training is often proportional to the frequency of target network updates[8] but excessive frequency/magnitude of target network updates leads to unstable training and worse final performance. How can we adapt the frequency of target network updates (or the moving average coefficient used to update the network) to maximize the training speed? Are there better ways to update the target network than a simple replacement or a moving average over time? Are there other ways to stabilize training which does not limit the learning speed (e.g. clipped objective similar to the one used in PPO (Schulman et al., 2017b))?

[8]Or to $1/(1 - \text{averaging\_coefficient})$ if target networks is computed using a moving average of the main network's parameters.

HER + multi-step returns HER generates data which is extremely off-policy[9] and therefore multi-step returns can not be used unless we employ some correction factors like importance sampling. While there are many solutions for dealing with off-policies of the data (e.g. Munos et al. (2016)), it is not clear if they would perform well in the setup where the training data is so far from being on-policy. Another approach would be to use multi-step optimality tightening inequalities (He et al., 2016). Using multi-step returns can be beneficial because the decreased frequency of bootstraping can lead to less biased gradients. Moreover, it accelerates the transfer of information about the returns backwards in time which, accordingly to our experiment, is often the limiting factor in DDPG+HER training (compare previous paragraph).

On-policy HER How to combine HER with state-of-the-art on-policy RL algorithms like PPO (Schulman et al., 2017b)? Some preliminary results with vanilla Policy Gradients were presented by Rauber et al. (2017), but this approach needs to be tested on more challenging environments like the ones proposed in this report. One possible option would also be to to use techniques similar to the ones employed in IPG (Gu et al., 2017).

Combine HER with recent improvements in RL It would be interesting to see how recent improvements in RL perform while combined with HER. The list of potential improvements is long e.g. Prioritized Experience Replay (Schaul et al., 2015b), distributional RL (Bellemare et al., 2017), entropy-regularized RL (Schulman et al., 2017a), or reverse curriculum generation (Florensa et al., 2017).

RL with very frequent actions RL algorithms are very sensitive to the frequency of taking actions which is why frame skip technique is usually used on Atari (Mnih et al., 2015). In continuous control domains, the performance goes to zero as the frequency of taking actions goes to infinity, which is caused by two factors: inconsistent exploration and the necessity to bootstrap more times to propagate information about returns backward in time. How to design a sample-efficient RL algorithm which can retain its performance even when the frequency of taking actions goes to infinity? The problem of exploration can be addressed by using parameters noise for exploration (Plappert et al., 2017) and faster information propagation could be achieved by employing multi-step returns. Other approach could be an adaptive and learnable frame skip.

References

Andrychowicz, M., Wolski, F., Ray, A., Schneider, J., Fong, R., Welinder, P., McGrew, B., Tobin, J., Abbeel, O. P., and Zaremba, W. (2017). Hindsight experience replay. In *Advances in Neural Information Processing Systems*, pages 5055–5065.

Bellemare, M. G., Dabney, W., and Munos, R. (2017). A distributional perspective on reinforcement learning. *arXiv preprint arXiv:1707.06887*.

Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., and Zaremba, W. (2016). Openai gym. *arXiv preprint arXiv:1606.01540*.

Dhariwal, P., Hesse, C., Klimov, O., Nichol, A., Plappert, M., Radford, A., Schulman, J., Sidor, S., and Wu, Y. (2017). OpenAI Baselines. `https://github.com/openai/baselines`.

Florensa, C., Held, D., Wulfmeier, M., and Abbeel, P. (2017). Reverse curriculum generation for reinforcement learning. *arXiv preprint arXiv:1707.05300*.

Gu, S., Lillicrap, T., Ghahramani, Z., Turner, R. E., Schölkopf, B., and Levine, S. (2017). Interpolated policy gradient: Merging on-policy and off-policy gradient estimation for deep reinforcement learning. *arXiv preprint arXiv:1706.00387*.

He, F. S., Liu, Y., Schwing, A. G., and Peng, J. (2016). Learning to play in a day: Faster deep reinforcement learning by optimality tightening. *arXiv preprint arXiv:1611.01606*.

Kingma, D. and Ba, J. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.

[9]Notice that normally off-policy data used by RL algorithms come from an earlier version of the policy and therefores is relatively close to on-policy data. It is not the case for HER, because we completely replace the goals which are fed to the network.

Levy, A., Platt, R., and Saenko, K. (2017). Hierarchical actor-critic. *arXiv preprint arXiv:1712.00948*.

Lillicrap, T. P., Hunt, J. J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., and Wierstra, D. (2015). Continuous control with deep reinforcement learning. *arXiv preprint arXiv:1509.02971*.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., Ostrovski, G., et al. (2015). Human-level control through deep reinforcement learning. *Nature*, 518(7540):529–533.

Munos, R., Stepleton, T., Harutyunyan, A., and Bellemare, M. (2016). Safe and efficient off-policy reinforcement learning. In *Advances in Neural Information Processing Systems*, pages 1054–1062.

Plappert, M., Houthooft, R., Dhariwal, P., Sidor, S., Chen, R. Y., Chen, X., Asfour, T., Abbeel, P., and Andrychowicz, M. (2017). Parameter space noise for exploration. *arXiv preprint arXiv:1706.01905*.

Pong, V., Gu, S., Dalal, M., and Levine, S. (2018). Temporal difference models: Model-free deep rl for model-based control. *International Conference on Learning Representations*.

Rauber, P., Mutz, F., and Schmidhuber, J. (2017). Hindsight policy gradients. *arXiv preprint arXiv:1711.06006*.

Schaul, T., Horgan, D., Gregor, K., and Silver, D. (2015a). Universal value function approximators. In *Proceedings of the 32nd International Conference on Machine Learning (ICML-15)*, pages 1312–1320.

Schaul, T., Quan, J., Antonoglou, I., and Silver, D. (2015b). Prioritized experience replay. *arXiv preprint arXiv:1511.05952*.

Schulman, J., Abbeel, P., and Chen, X. (2017a). Equivalence between policy gradients and soft q-learning. *arXiv preprint arXiv:1704.06440*.

Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O. (2017b). Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*.

Todorov, E., Erez, T., and Tassa, Y. (2012). Mujoco: A physics engine for model-based control. In *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, pages 5026–5033. IEEE.

A Goal-based API Examples

Exposed reward function The following example demonstrates how the exposed reward function can be used to re-compute a reward with substituted goals. The info dictionary can be used to store additional information that may be necessary to re-compute the reward but that is independent of the goal, e.g. state derived from the simulation.

```
import gym

env = gym.make('FetchReach-v0')
env.reset()
obs, reward, done, info = env.step(
    env.action_space.sample())

# The following always has to hold:
assert reward == env.compute_reward(
    obs['achieved_goal'], obs['desired_goal'], info)

# ... but you can also substitute goals:
substitute_goal = obs['achieved_goal'].copy()
substitute_reward = env.compute_reward(
    obs['achieved_goal'], substitute_goal, info)
```

Compatibility with standard RL algorithms The following example demonstrates how to wrap the new goal-based environments to make their observation spaces compatible with existing implementations. To do so, simply wrap any goal-based environment with `gym.wrappers.FlattenDictWrapper` and specify the desired keys of the dictionary that you would like to use.

```
import gym

env = gym.make('FetchReach-v0')
print(type(env.reset()))
# prints "<class 'dict'>"

env = gym.wrappers.FlattenDictWrapper(
    env, ['observation', 'desired_goal'])
ob = env.reset()
print(type(ob), ob.shape)
# prints "<class 'numpy.ndarray'> (13,)"
```

B Hyperparameters

To ensure a fair comparison, we perform a hyperparameter search over the following parameters:

- Actor learning rate: $\{1 \cdot 10^{-4}, 3 \cdot 10^{-4}, 6 \cdot 10^{-4}, 1 \cdot 10^{-3}, 3 \cdot 10^{-3}, 6 \cdot 10^{-3}, 1 \cdot 10^{-2}\}$
- Critic learning rate: $\{1 \cdot 10^{-4}, 3 \cdot 10^{-4}, 6 \cdot 10^{-4}, 1 \cdot 10^{-3}, 3 \cdot 10^{-3}, 6 \cdot 10^{-3}, 1 \cdot 10^{-2}\}$
- Polyak-averaging coefficient τ: $\{0.9, 0.93, 0.95, 0.97, 0.99\}$
- Batch size: $\{32, 64, 128, 256\}$
- Probability of random action: $\{0, 0.1, 0.2, 0.3, 0.4\}$
- Scale of additive Gaussian noise: σ: $\{0, 0.1, 0.2, 0.3, 0.4\}$
- Action L2 norm coefficient: $\{0, 0.01, 0.03, 0.1, 0.3, 0.6, 1.\}$

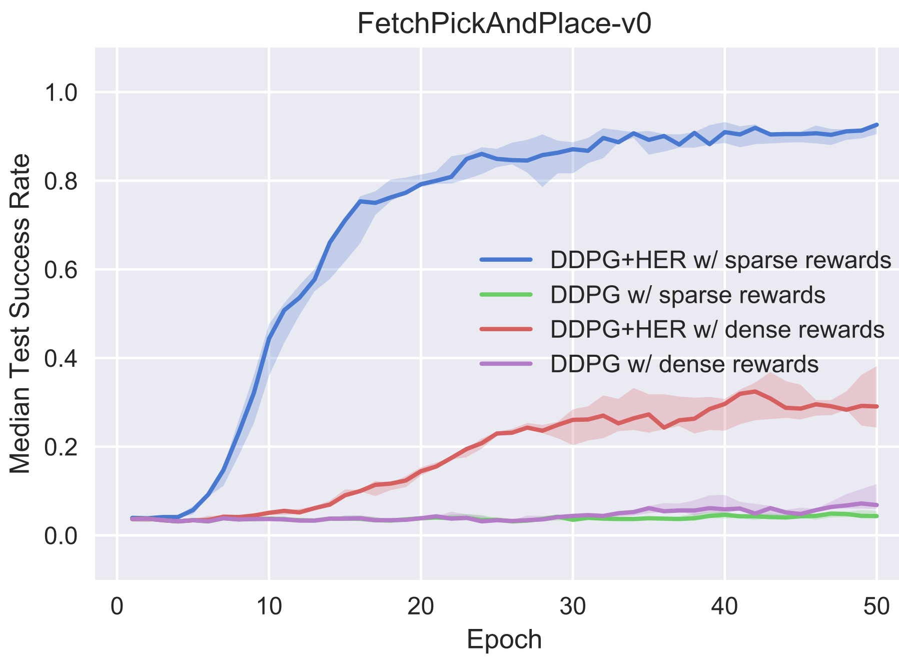
Since searching all possible combinations exhaustivley is intractable, we randomly sample 40 combinations and train a policy on the `HandManipulateBlockRotateZ-v0` environment for all four configurations (DDPG+HER sparse, DDPG+HER dense, DDPG sparse, DDPG dense). We picked this environment since all configurations are capable of learning on this environment. For each configuration and combination we train with 3 random seeds and average performance across this. To select the best hyperparameter combination, we numerically compute the area under the test success rate curve and select the combination that achieves the best performance across all tasks.

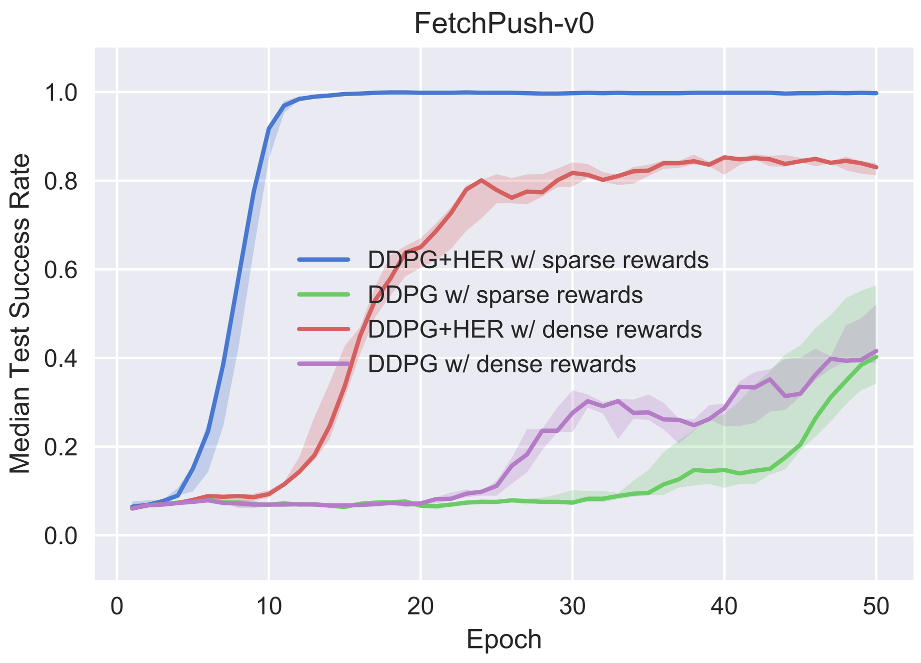
All experiments in this paper use the following hyperparameters, which have been found by the aforementioned search:

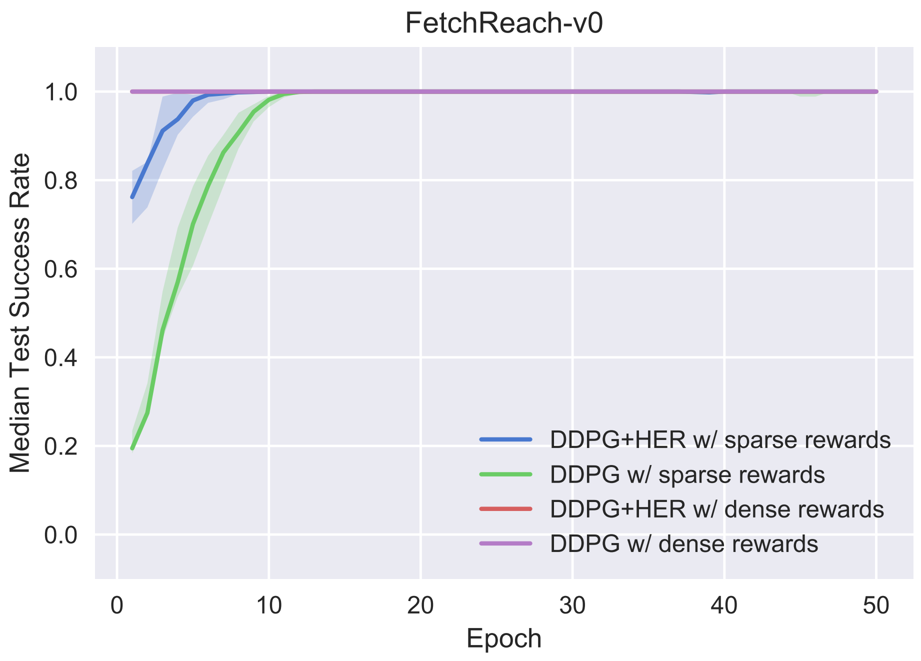
- Actor and critic networks: 3 layers with 256 units each and ReLU non-linearities
- Adam optimizer (Kingma and Ba, 2014) with $1 \cdot 10^{-3}$ for training both actor and critic
- Buffer size: 10^6 transitions
- Polyak-averaging coefficient: 0.95
- Action L2 norm coefficient: 1.0
- Observation clipping: $[-200, 200]$
- Batch size: 256
- Rollouts per MPI worker: 2
- Number of MPI workers: 19
- Cycles per epoch: 50
- Batches per cycle: 40
- Test rollouts per epoch: 10
- Probability of random actions: 0.3
- Scale of additive Gaussian noise: 0.2
- Probability of HER experience replay: 0.8
- Normalized clipping: $[-5, 5]$

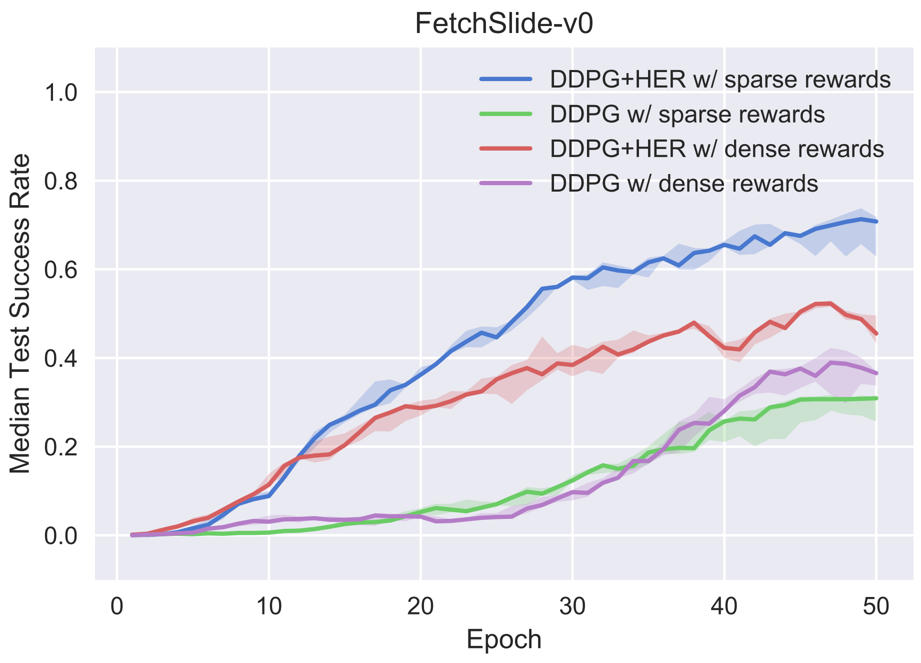
All hyperparameters are described in greater detail in Andrychowicz et al. (2017).

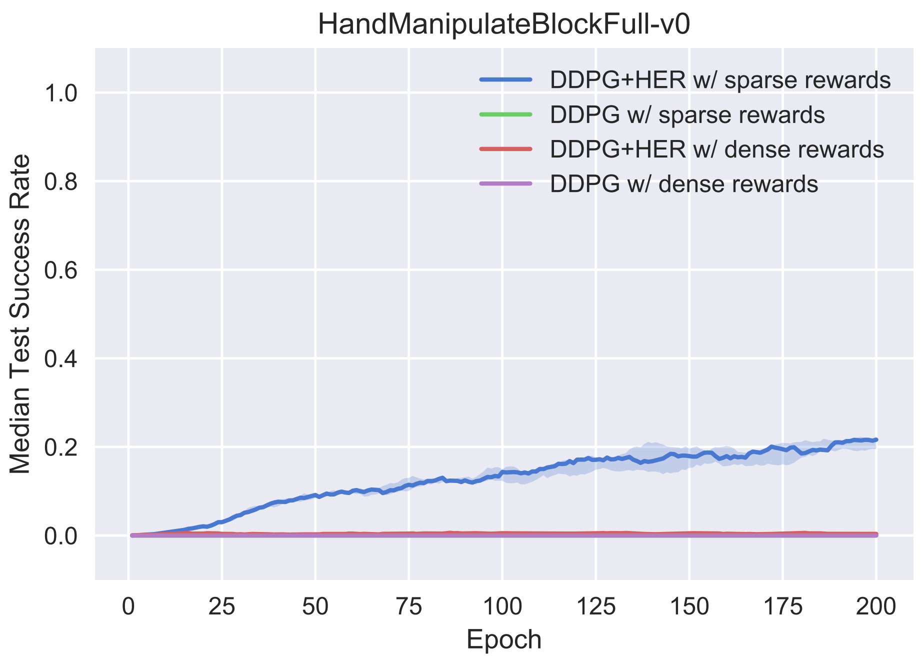
C Full Benchmark Results

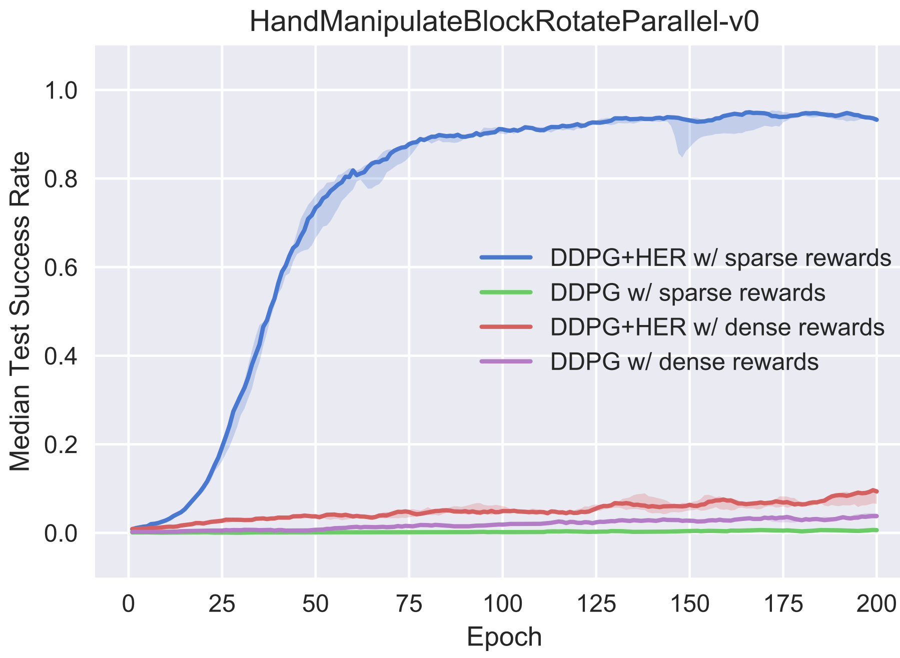


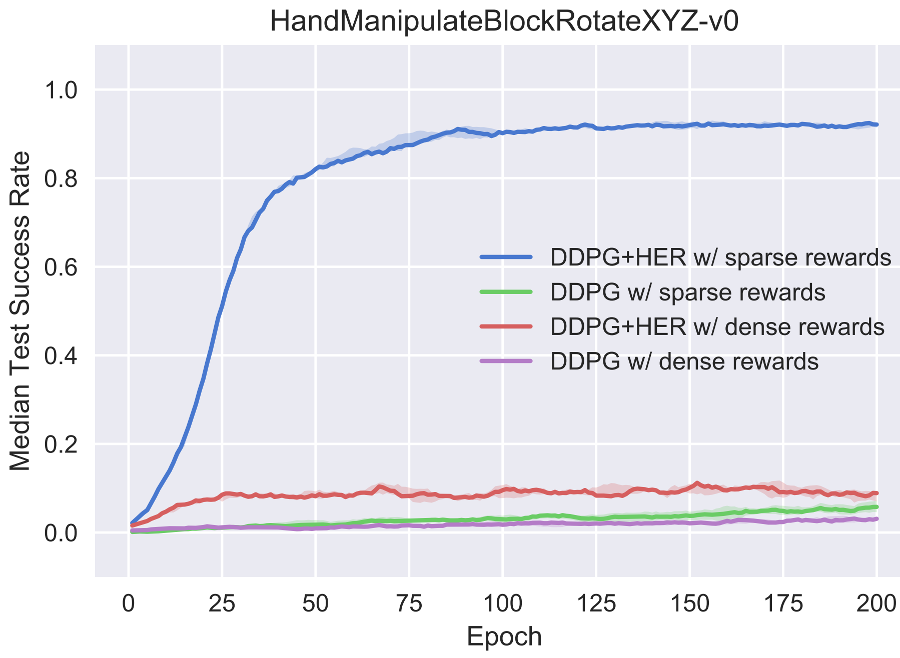

FetchPush-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards

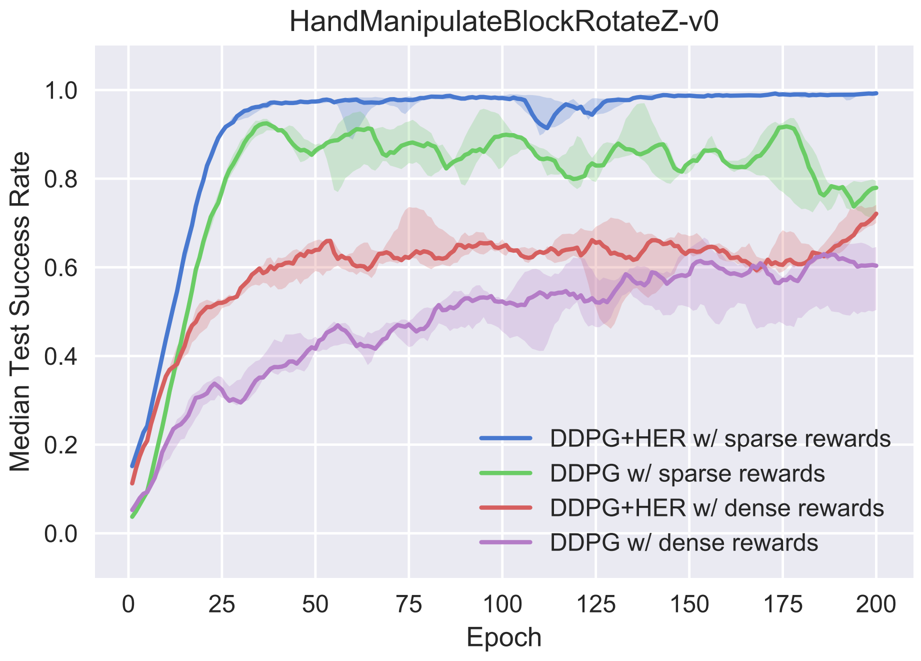

FetchReach-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards

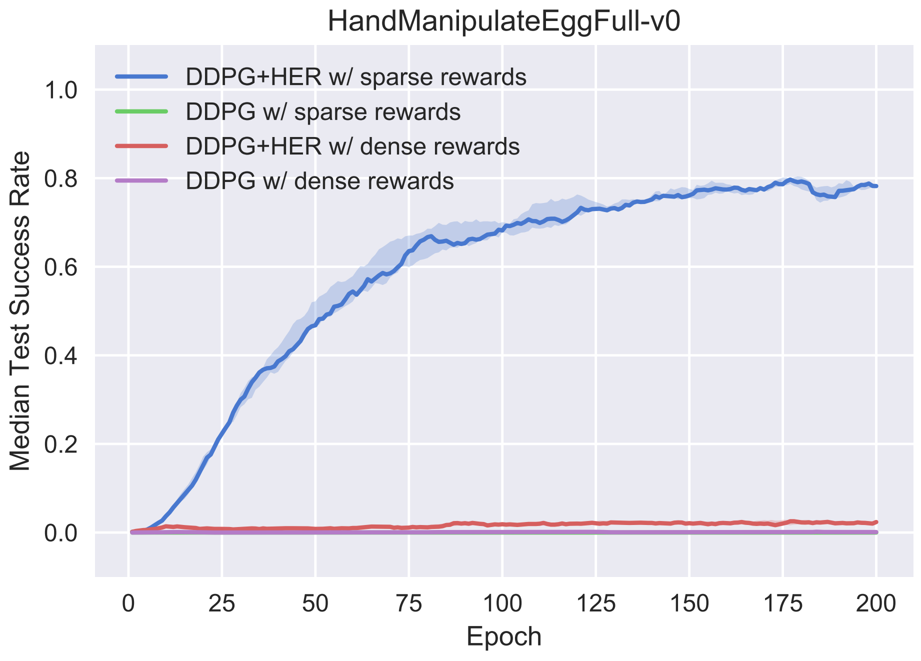

FetchSlide-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards

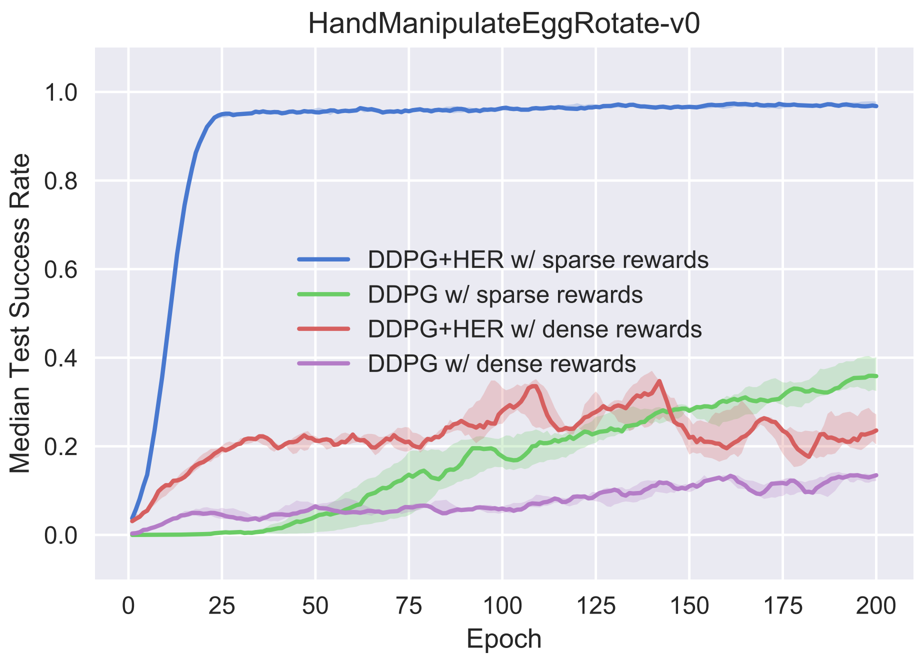

HandManipulateBlockFull-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards

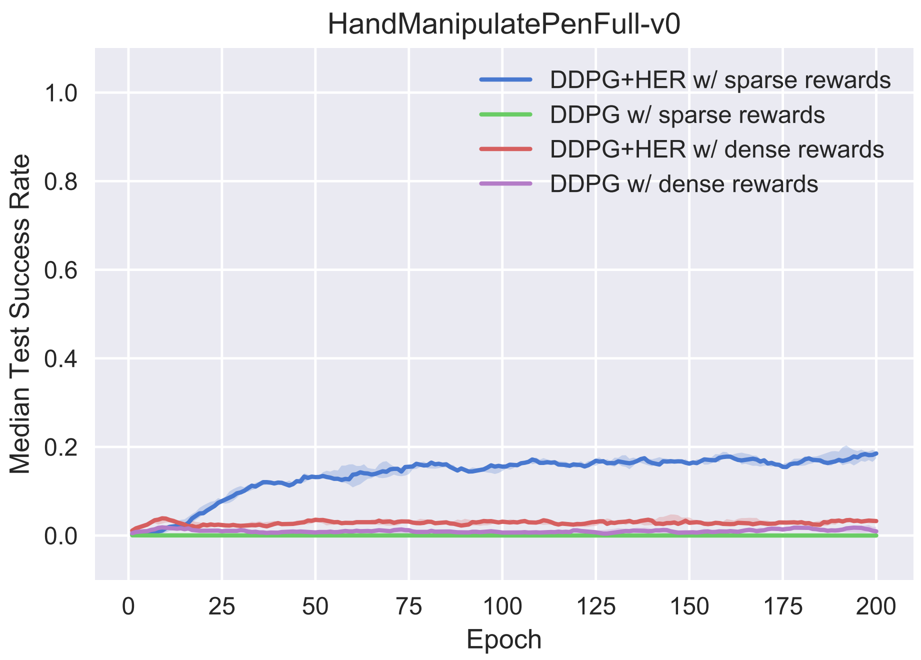

HandManipulateBlockRotateParallel-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards
1.0
0.8
0.6
0.4
0.2
0.0
0
25
50
75
100
125
150
175
200

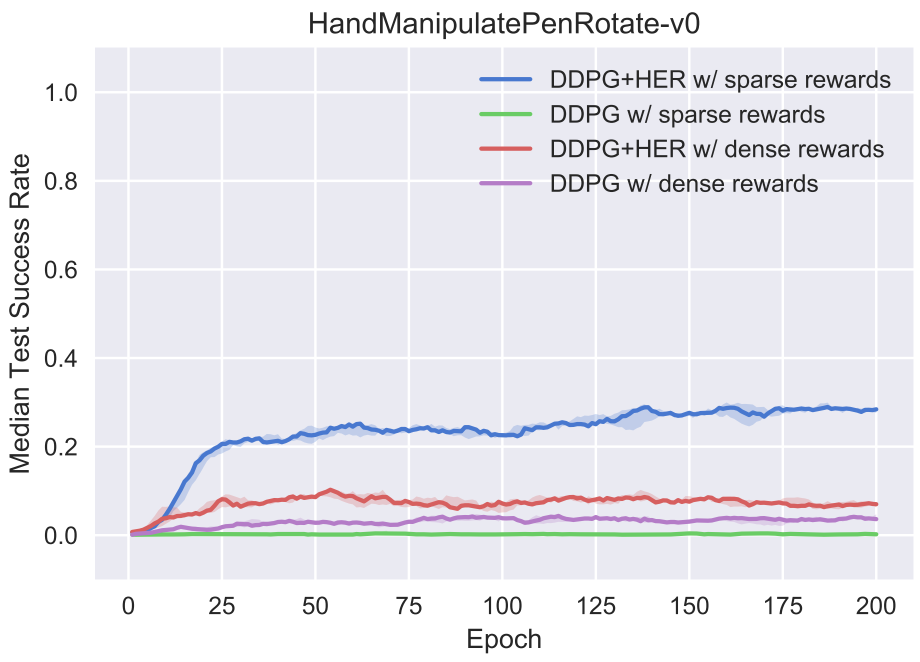

HandManipulateBlockRotateXYZ-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards
1.0
0.8
0.6
0.4
0.2
0.0
0
25
50
75
100
125
150
175
200


HandManipulateBlockRotateZ-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards


HandManipulateEggFull-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards


HandManipulateEggRotate-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards


HandManipulatePenFull-v0
Median Test Success Rate
Epoch
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards


HandManipulatePenRotate-v0
DDPG+HER w/ sparse rewards
DDPG w/ sparse rewards
DDPG+HER w/ dense rewards
DDPG w/ dense rewards
Median Test Success Rate
Epoch
0.0
0.2
0.4
0.6
0.8
1.0
0
25
50
75
100
125
150
175
200