DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis in Informatics

Branch Dueling Deep Q-Networks for Robotics Applications

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I confirm that this master's thesis in informatics is my own work and I have documented all sources and material used.

Munich, 15.07.2020 Baris Yazici

Acknowledgments

Abstract

Kurzfassung

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1. Introduction

1.1. Objectives

Manipulation of objects is one the most inherent action of the humankind. Humans never stood and plan about how to manipulate an object. It is a natural instict for humans to grab objects in certain ways. Even an infant human can easily manipulate different shapes and colors of objects. Manipulation helps us to use tools, gadget to achieve tasks and provide service. Therefore, manipulation skills will be central for robots of any kind. From rehabilitation to service robots, tool usage is vital to enable them to achieve their objective. Our daily manipulation tasks are shown in figure 1.1. For a complicated manipulation task first of all grapsing the object is essential. We need to first firmly grasp a water bottle to drink it. Without a firm grasp the safety of the manipulation process is projected to risk.

Nowadays, every kinds of robots are helping us produce in the industry. However, those robots at the manufacture facilities are only capable of doing same repetitive task. The task they are responsible of expands the car manufacturing to high precision microchip producing. On all those tasks robots are extremely efficient and precise. On the other hand, if a the car company decides to manufacture a new model of car with a slightly different chasis the whole process needs to be changed and program of the robots needs to be hardcoded from zero. Hardcoding every move of the robot in a slight change of a task is fundementally opposes the very nature of the robots. Main objective of this master's thesis is to enable robotic manipulators to incrementally learn to grasp tools and generalize the learned policy to unseen objects. Rather than overfitting to a certain set of objects, we measure the success rate on unseen dataset. This preassumption promises a robust actor that can adapt well on unseen object and environments.

1.2. Contribution

This projects provides two main boiler plate for developers. Firstly well documented and tested robot gripper environment based on Open AI Gym interface[**openai gym**]. Gym Environment provides easy to use interface to interact. Moreover, gripper environment complies with the most standard and well documented libraries such as python3, pybullet and numpy. Secondly, we present a novel implementation of BDQ reinforcement algorithm algorihtm adopted to most used Stable Baselines project[2].

Figure 1.1.: Different manipulation skill adopted to robotic manipulators [1]

1.3. Challenges

1.4. Report Layout

2. Background

2.1. Related Works

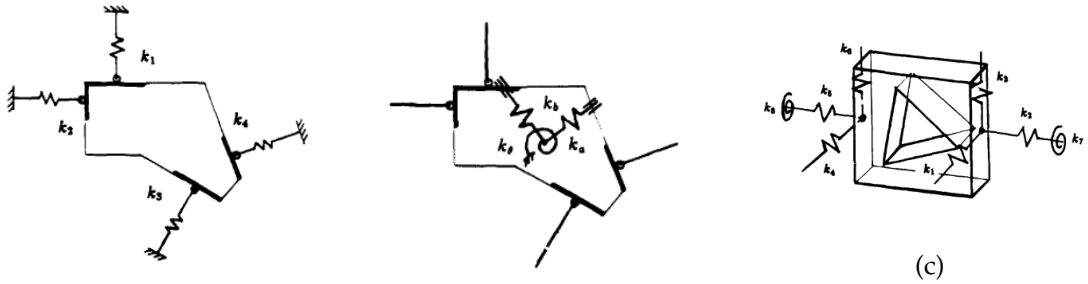
Robot manipulation and grasping is an intensively researched area. The wide span of the subject makes it hard to categorize all different approaches under one umbrella. Nevertheless, analytical and empirical grasping approaches tend to be the most used categorization in the literature [3].

2.1.1. Analytical Grasping Approach

The analytical approach has been introduced first by Nguyen. He tries to solve the grasping problem by defining analytical objectives. Such as a successful grasp should achieve force closure and satisfy the stability conditions by closing the object from each direction [4]. Nguyen models the hand and the object, to be grasped, to compute the stable force closure grasp analytically. This kind of analytical techniques comes with an exhaustive computation burden. Although the proposed algorithm works fast and correct when the object is planar and flat with a small number of faces, they don't scale to household objects such as mugs or bottles [3]. Moreover, in most robotics setups full geometrical models of the objects are not available [5].

2.1.2. Empirical Grasping Approach

The empirical grasping approach introduced to overcome the difficulties faced with the analytical grasping approach. Empirical methods include learning, which is based on sampling and then training. Some examples of empirical grasping approaches are imitating a human teacher [6], learning from the handcrafted features [7], and deep reinforcement learning(RL) technique to learn close-loop dynamic visual grasping strategies [8]. Imitating a human teacher can easily learn the demonstrated training data. However, it has difficulties to scale to the novel objects, which were not seen during the training [3]. Saxena et al.'s technique to learn from the feature effectively generalize to unseen objects but it fails to choose the best grasp for a particular task [3]. RL approaches learn a particular grasp of an object based on a definition of a goal. Thus, the learned grasp of an object already linked to the task's goal. The flexibility of RL made itself attractive among grasping researchers. One disadvantage of the RL approach is that, it requires a considerable amount of data to train. Although recent applications introduced randomization for sim-to-real transfer of the models [9], it still has difficulties to perform reliably in the real-world [10].



(a) (b) (c)

Figure 2.1.: Stable force closure examples fingers are represented as virtual springs. Nguyen proved that all force closures can modified to be a stable grasp candidate[4].

2.2. Learning applications on grasping

Experts implement handcrafted features and hand-coded controllers. Thus, it is time-consuming and incapable of generalizing to new objects and scenery. Among all other approaches, machine learning applications on grasping has proven to give a high success rate on novel objects.

2.2.1. Deep Learning for Detecting Grasps candidates

Lenz et al. propose a five parameters model trained by supervised learning from the candidate grasps database. They draw a rectangle box representing the best grasp location with the five-dimensional parameter model, x, y coordinates, width, height, and orientation.

Their cascaded network architecture bypasses the need for a handcrafted features. After training, the first layer network learns low-level features and delivers possible naïve grasping candidates, and the second layer chooses the top-ranked grasping candidate 2.2.

Although they achieved up to 90% success rate on grasping Lab tools, this method is limited to only parallel plate gripper. When one wants to use another gripper type, the dataset should be updated entirely for that gripper. Besides data collection process is time-consuming and biased

2.2.2. Dex-net

[(TODO: Architectur'i anlat. Robustness factor nasil parametirize edildi?)]

Another approach for grasping is to learn the grasp robustness factor. Mahlet etal trained convolutional neural networks to learn the grasps robustness function from 6.7 million point cloud data. They collect the data similarly to Lenz et al. with an analytical

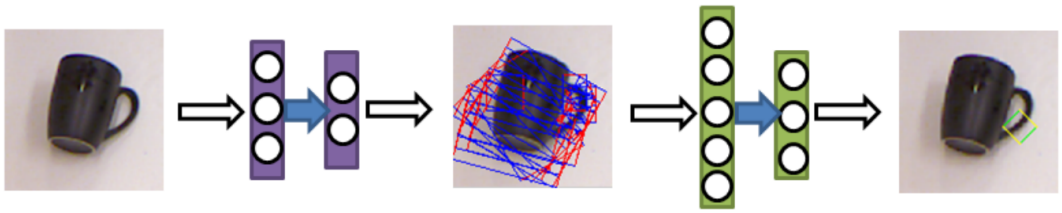


Figure 2.2.: Red-blue rectangles represent possible grasp candidate. Green rectangle is the top-ranked grasp rectangle [11]

grasp metric to evaluate the quality of a grasp.

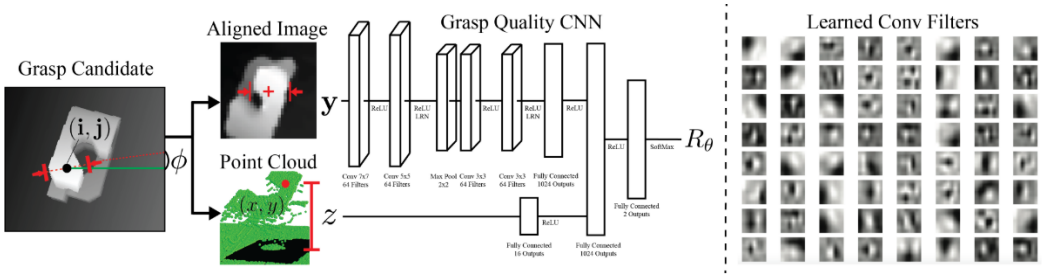


Figure 2.3.: Dex-net architecture [11]

With 98% success rate, their approach indeed proved to be robust. However, the designed network only outputs the grasp location such that a grasp planning algorithm is needed to complete the grasping process. Moreover, data collection can be tedious due to a large number of a machine-labeled dataset.

2.2.3. Deep Reinforcement Learning for Vision-Based Robotic Grasping: A Simulated Comparative Evaluation of Off-Policy Methods

The sequential decision-making process is inherent in all grasp tasks. This property of grasping helps us to model it with a reinforcement learning framework. Unlike other works, this approach trains end-to-end policies to automatically learn to grasp without any prior knowledge about the environment or the gripper model. Moreover, the end-to-end nature of their system eliminates the need for additional grasp planner, which was a default in previous works. Quillen et al. show that off-policy RL can increase the robustness of grasping models. Based on their investigation, corrected Monte Carlo and Deep Q Learning outperform the earlier supervised learning approach. They observe that model-free RL approaches allow pre-grasp manipulation to increase the chances of grasp in future actions.

They suit one complete network to concatenate perception input and actions from two different branches 2.6. Although the number of parameters increases drastically with convolutional layers from the perception branch, it makes the system more compact and

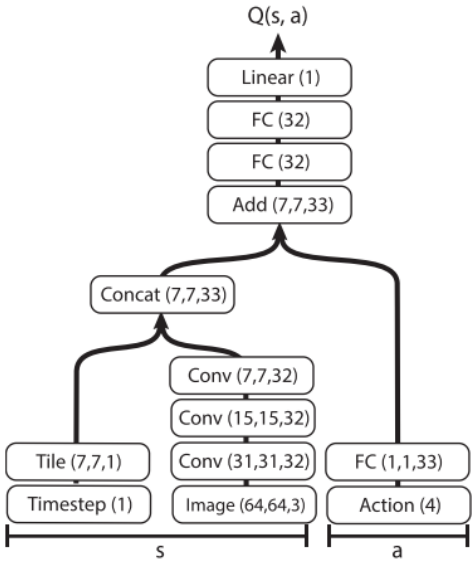


Figure 2.4.: Deep Learning network architecture of [12]

easier to understand.

2.2.4. Comparing Task Simplifications to Learn Closed-Loop Object Picking Using Deep Reinforcement Learning

The learning setup is similar to the Quillen et al. with one robot gripper and randomly spawned objects in the simulation. One significant difference regarding the learning setup is Breyer et al. generates the robot gripper only until the wrist without the rest of the arm and, therefore, doesn't need to calculate the inverse kinematics equation.

Breyer et al. enhanced the RL based data-driven grasp approach with Curriculum Learning and the introduction of auto-encoder for perception. Thanks to the curriculum learning setup, which increases the task difficulty based on the agent's current performance, they shortened the time for the agent to explore the environment. In other words, curriculum learning guides the agent throughout its learning phase. Besides, with the help of autoencoder for the perception layer, their network tends to spend less time to comprehend the observation compare to the Quillen et al.'s approach.

Unlike Quillen et al., they experimented with policy-based on-policy RL algorithm, TRPO. Policy -based algorithms tend to **[(TODO: Policy based vs. value based here not exploration)]** explore better than epsilon greedy based exploration. This property may also contribute to the higher success rate and faster convergence. After training grasping models on simulation, they tested them on a real robot. Although they didn't use domain randomization to minimize the reality gap, they achieved up to 78% success rate.

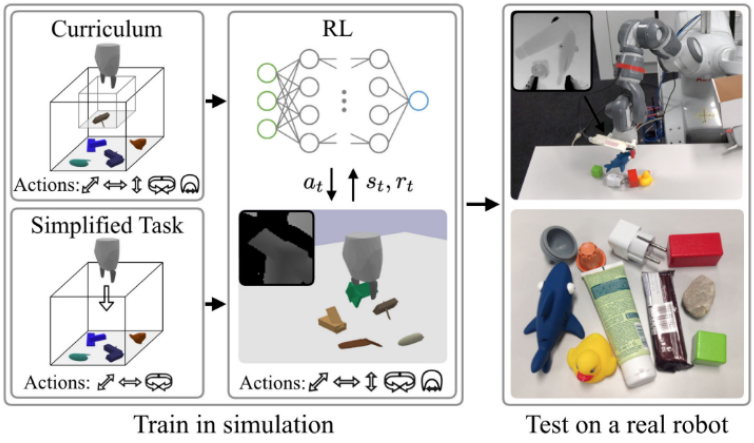


Figure 2.5.: Breyer et al. [13]

2.2.5. Solving Rubik's Cube With a Robot Hand

OpenAI et al. present a novel approach for in-hand manipulation problems. Their system attacks Sim2Real discrepancy between simulated models performing on real robots.

Training the Deep RL models on simulation is becoming more and more common. The popularity of simulation increases the demand for enhanced Sim2Real model transfer algorithms. Domain randomization has shown great success in bridging the gap between reality and simulation [14]. More researchers implement machine learning methods that randomize the environment and gripper material parameters. Through this approach, trained models can achieve higher generalization property with robustness to increasing noise on the sensor or environment settings. OpenAI proposes a Meta-Learning method with policies that involve memory like recurrent neural networks that can learn the underlying dynamics of the environment—combining meta-learning with automated domain randomization algorithm results on an enhanced adaptation of models on real-world robots.

2.3. Reinforcement Learning

The simplest examples of learning come from our own life; we learn to walk, speak the language, or to cook. All those activities span our entire life, it influences who we are and the decisions we take in life. We know that living animals such as mammals learn from their social and asocial interactions with the environment [16]. Although we have not yet developed a full-scale theory of animal learning, we have developed computational objectives for machines to learn [17]. This computational approach falls into three categories as Supervised, Unsupervised, or Reinforcement Learning.

In this chapter, we will consider the Reinforcement Learning objectives and problem formulation. Reinforcement Learning provides a systematic approach to maximize the

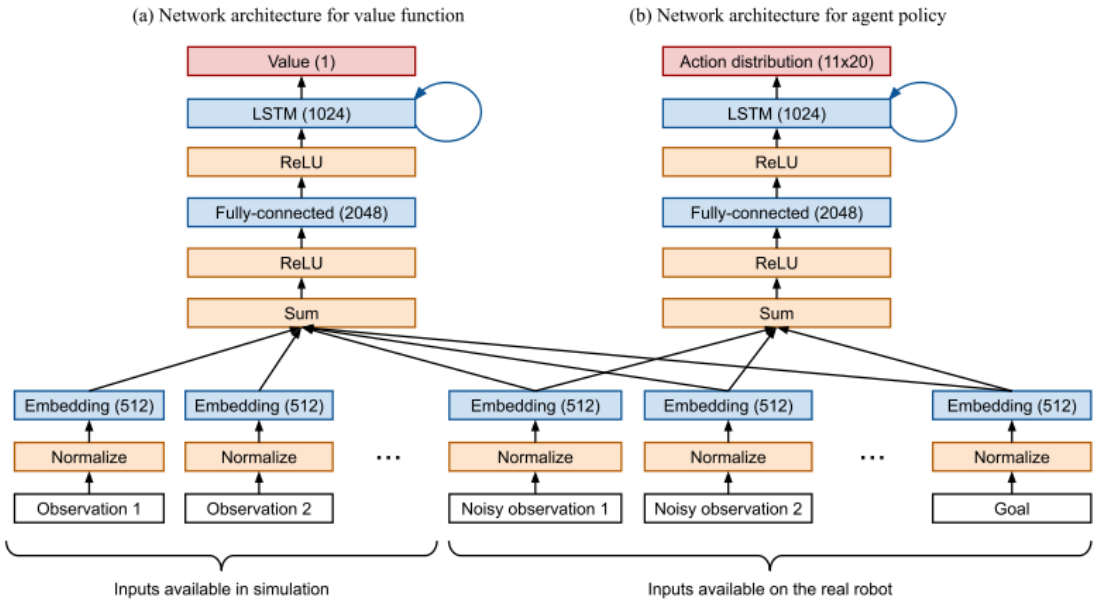


Figure 2.6.: OpenAI policy and value network architecture [15]

reward by linking observations to actions. A reinforcement learning agent creates its data by interacting with the environment. Therefore, it is fundamentally different from supervised and unsupervised learning, where the data is already provided [17]. Another important difference is the inherent goal-oriented approach. Reinforcement learning agent maximizes the rewards for its inherent general goal. Other machine learning approaches lack this goal [17]. For instance, supervised learned software recognizing faces can be used for security reasons to detect criminals or can be easily used to unlock phones. However, a reinforcement learning agent trained to drive a car autonomously can only drive a car. In a sense, reinforcement learning provides us end-to-end learning.

A core feature of reinforcement learning is that it acts on uncertain environments and, in return, receives the observation and reward. Fundamentally, a learning agent collects this experience and tunes its action to increase the expected reward. The expected reward term refers to the end of the horizon. For example, a chess-playing agent can choose to sacrifice the queen in the next move for a checkmate in the move after. In this case, the reward would decrease when the agent loses a queen, but the goal of the agent will be satisfied by terminating the game. For a well-defined reinforcement learning system, we can speak of four main components: Policy to decide the actions, a reward to maximize the expected reward in the horizon, and a model of the environment, telling which directions the chess pieces can move. The components of reinforcement learning are formulated based on Markov Decision Process. In the MDP chapter, we will detailly explain RL components. In the next chapters first Markov Chains, the simple version of MDP, then MDP, the slightly advanced version of Markov Chains, will be explained by some simple modifications [18].

2.3.1. Markov Chain

The weak law of large numbers has a tremendous significance on stochastic modeling. This law states that the average of a large number of experimentations converges to the real value of the probability of a particular task. As an example, if one tosses infinite amounts of the coin, the average number of heads should converge to 0.5 [19]. Bernoulli's weak law of large numbers only covers independent events. Markov proved that Bernoulli's law also holds on dependent cases [19]. As the law of large numbers suggests, if one conducts a large number of iterations on this problem, one can deduce the transition matrix. This matrix proves to be the only information one needs to compute the next state. This characteristic defines the famous Markov property; the current state captures all the necessary information one needs to predict the next state. If we extrapolate this example to slightly complex systems, for example, weather forecast, we just need today's weather report to predict tomorrow's forecast, assuming that we know the transition matrix. Naturally, one can formulate other events with Markov Chain lawnmower, and random walk are the straightforward ones in the literature[19].

It is also possible to attach rewards to Markov Chain's formulation. In figure 2.7, the transition between states is represented with the arcs. And each transition has a probability similar to the transition matrix; we defined before. Each state has an immediate reward and a value function. The immediate reward is received directly when the actor moves to that state. The value of a state represents how likely the future actor will end up collecting high rewards.

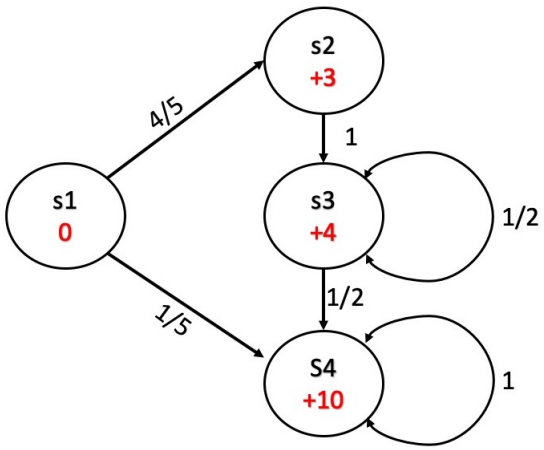


Figure 2.7.: Markov chain with transition probabilties and rewards

The value of a state will be later significant to solve Reinforcement Learning problems through Value Iteration methods. They are one of the essential algorithms that led to the initial success of Reinforcement Learning research.

2.3.2. Markov Decision Process

Markov decision process is a slightly advanced version of the Markov Chain. It includes action on top of the Markov Chain. Reinforcement learning problems are formalized as a Markov Decision Process rather than Markov Chain because RL agents are free to choose from different actions.

MDPs first came into play as part of optimal control problem by Bellman [20]. Bellman applied dynamic programming methods to solve the MDP problem optimally. However, this methodology was not scalable to larger problems stem from the curse of dimensionality problem **[Sutton]**.

The fundamental elements of MDP are as follows:

- Agent: The actor takes action on the environment to learn.
- Environment: The agent interacts with the Environment(Plant).
- Rewards: Environment returns rewards based on the interaction made by the actor.
- State: View of the environment from the eyes of the actor.

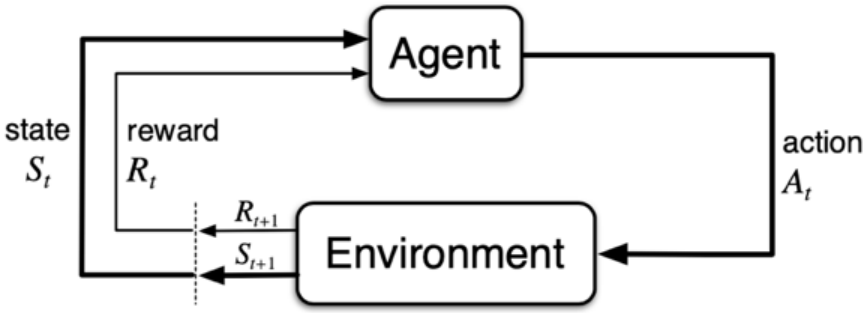


Figure 2.8.: MDP structure

The process of action follows; the agent acts on the environment at time t and environment return the reward and state of the action at time $t+1$. Based on the state of the environment at the $t+1$ agent makes another action A_{t+1}, which results in R_{t+2} and S_{t+2}.

In every MDP system, agents should be reachable to every state through a sequence of actions. The transition between states is of great value for the MDP framework. One can compute the transition probability in MDP, given the inner dynamics of the environment [17]. The below equation defines the internal dynamics probability. It tells, how probable it is to end up in state s' with reward r by taking action a in state s.

$$p(s', r|s, a) = Pr\{S_t = s', R_t = r|S_{t-1} = d, A_{t-1} = a\} \tag{2.1}$$

One can calculate the transition probability function from the inner dynamics' probability function.

$$p(s'|s,a) = Pr\{S_t = s'|S_{t-1} = s, A_{t-1} = a\} = \sum_{r \in R} p(s', r|s, a) \tag{2.2}$$

Next chapter, we will dive into the definition of the reward and value function. Based on those concepts we will build the logic on how to solve MDPs optimally

2.3.3. Reward and Value function

[(TODO: Ilk paragraf)]

As defined in the Markov Chain section, rewards and value functions are the essence of value iteration algorithms. In this section, we will describe the objective of the RL problem formally. As we mentioned in previous chapters, we want the increase the number of rewards we achieve when we reach the terminal state. If we define the reward at final state T as R_T and the reward at the initial state t is R_t, returns we receive is the sum of rewards in every state.

$$G_t = R_{t+1} + R_{t+2} + R_{t+3} + ... + R_T \tag{2.3}$$

G_t is the notation of expected return. We will mostly use the discounted version of the expected return calculation. We introduce a discount factor (γ, to value the rewards that the agent receives now, compare to the rewards in the future.

$$G_t = R_{t+1} + \gamma^1 * R_{t+2} + \gamma^2 * R_{t+3} + ... + \gamma^T - 1 * R_T = \sum_{k=0} \gamma^k R_{t+k+1} \tag{2.4}$$

For instance, if a rational human offered 1m Euros now, versus 1m Euros in 50 years, would usually choose 1m Euros now. Therefore, our agent also weighs the rewards it receives now, over 50 steps from the current state. In the meantime, we do not want the agent to undervalue the importance of reaching the terminal state through the highest reward sequence. Given the below example, if we introduce a discount factor of 0, the agent will always try to maximize the immediate reward and take a sequence of s1-a2-s3-a4-s4 and end up with non-optimal greedy algorithm with $G_t = 20$. But with a discount factor, in this example everything between $0 < \gamma < 1$ works, would find the optimal sequence(s1-a1-s2-a3-s4) with $G_t = 25$.

The value function is the expectation of returns while an agent is following the policy (π). Policy namely represents the probability distribution of an agent taking action a in state s. The policy is similar to the transition probability matrix in the Markov Chain section. Using policy, we can define the value function of an agent following the policy pi as below.

2.3.4. Q-Learning

Q-learning algorithms have been the core of the RL research for almost 20 years. It combines the idea of TD learning in approximating action-value function. Through this

approach, the computation converges faster than state-value approximation algorithms. Another strength of the Q-learning algorithm is its off-policy nature. The Q-learning agent can learn from the results of different policies. Off-policy nature makes the agent more data-efficient. An agent is not obliged to learn from the outcome of one policy; instead, many policies can contribute to learning.

$$Q(S_t, A_t) \longleftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t))] \tag{2.5}$$

2.4. Function Approximation

As mentioned before, it is often not possible to find either the optimal policy or the optimal value function due to computational resources. It is usually enough to find approximate solutions. Various function approximators are available for us to use. The main categorization follows as; linear and nonlinear function approximators. Their working principle is similar; they both follow a specific policy and sample experiences. Based on the experiences they approximate either policy or the value function.

The application of neural networks provided RL methods a boost.(REFERENCE) Since the introduction of function approximators, the success of RL applications has increased significantly. Although function approximation tools bring convergency issues in some corner cases, it shows excellent success practically.

If one defines the value function under some weight parameterization, then the $V(s, w)$ notation replaces the $V(s)$. To find suitable weight parameters that represent the value function as general as possible, one needs to update parameters w at each step towards the smallest loss region based on a particular objective description. Firstly, we need to define an objective function and then find a method to tweak our weight parameters towards the objective gradually. There are a couple of possible objectives to learn in the literature; the state-value function, action-value function, or the directly the policy. In the case of the state value function, one can choose the objective function as the mean squared value loss between the estimated state-value function and the target state-value function (2.6). While for policy approximation, expected return represents the objective function 2.9.

(Silebilirim) Target state-value function can be the monte-Carlo or TD target. Monte Carlo's target is the expected return (G_t), and TD target is the bootstrapped value. The main difference between those targets is that Monte Carlo ensured to converge to a global optimum. In contrast, the bootstrapped TD target converges only to a local optimum near the global optimum. (Silebilirim)

$$VE(w) = \sum_{s \in S} \mu(s)[v_\pi(s) - \hat{v}(s, w)]^2 \tag{2.6}$$

Secondly, one needs a way to optimize the objective function. The stochastic gradient descent method is the most prominent solution to improve the weight parameters based

on a defined loss function. 2.7 shows one gradient update step of the stochastic gradient descent method on the weight vector.

$$w_{t+1} = w_t - \frac{1}{2}\alpha\nabla\Big[v_\pi(s) - \hat{v}(s,w)\Big]^2 \tag{2.7}$$

The optimal weight vector needs to find the right balance between strongly representing one state and generalizing to similar unseen states. As a result, our approximator needs to avoid either overfitting or underfitting.

One can also approximate action-value function in the same way as state-value function. The gradient update step of the action-value function is similar to the state-value function as in 2.8

$$w_{t+1} = w_t - \alpha\Big[U_t - \hat{q}(S_t, A_t, w_t)\Big]\nabla\hat{q}(S_t, A_t, w_t) \tag{2.8}$$

U_t being the target of the approximation can be either TD or Monte Carlo target.

So far, we have only considered the function approximation on the action and state functions. Another promising and popular technique is to approximate the policy function directly. Policy function can point us in a more direct way than action and state values. Since it directly aims to solve the problem at hand, to find the optimal policy [21]. The objective function of policy gradient methods is simply the expectation of total return under policy π.

$$J(\theta) = E\Big[\sum_{t=0}^{H} R(s_t, u_t)\Big] \tag{2.9}$$

$$\theta \leftarrow \theta + \alpha\nabla_\theta J(\theta) \tag{2.10}$$

2.4.1. Neural Networks

Neural networks are the unique case of function approximators. Although they follow the same procedure as SGD methods, their weight matrix is nonlinearly related to the approximated $V(S_t, w_at)$. Nonlinear relation brings convergency issues and problems with instabilities. However, the practical success of these kinds of methods shadows the weak theoretical basis.

A generic neural network(2.9) comprises layers of artificial neurons connected with weight, bias vectors, and activation functions to each other. Each activation function feeds nonlinearity to the general equation.

2.5. Value-Based Reinforcement Learning

Approximation of action-value or state-value function methods falls into the category of Value-based RL. These methods are model-free, meaning that they use sampling to solve the optimal solution for the problem [22]. At the same time, they are off-policy

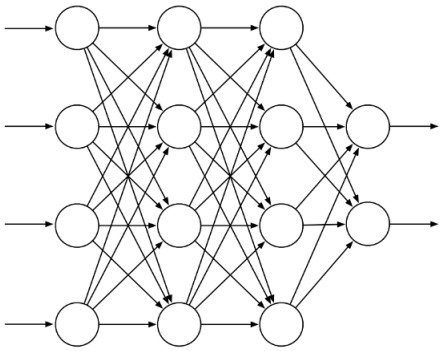


Figure 2.9.: Generic neural network with two hidden layers

algorithms, which makes them data efficient but high variance algorithms [21]. The fact that these methods only indirectly optimize the policy make them unstable during the learning phase [17]. Value function-based approaches can overestimate the selected actions from the policy, which is the typical problem with Q-learning based algorithms.

2.5.1. DQN

DQN is the neural network extension of the Q-learning algorithm. It has shown RL can handle high dimensional nonlinear control problems. DQN optimizes Bellman error by parameterizing the action-value function. Some extensions of DQN introduced experience replay buffer to cope with the high variance problem [23]. [22] inputs randomly collected mini batches of experiences to the neural network consisting of multiple layers. Thanks to their neural network structure, they overcome the convergency issues.

$$L(\theta) = E_{(s,a,r,s')\sim U(D)}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^{-})) - Q(s, a; \theta)\right)^2\right] \tag{2.11}$$

2.6. Policy-Based RL

Policy-based solutions directly parameterize the policy to find the optimal policy which returns the highest reward. These approaches proved to be more stable than Value-based counterparts. One reason behind stability is that actions are sampled from the continuous policy parameterization function, which outputs smooth action probabilities [17]. Similar to Value-based methods, policy-based RL also aims to solve the RL problem only with sampling in model-free fashion.

2.6.1. Policy Gradient

Policy gradient methods incorporate stochastic gradient ascent on policy objective function. This update optimizes the theta parameters of the policy. Unlike DQN, policy

gradient methods perform each update in on-policy fashion. It uses only the experiences taken under the particular policy to update the parameters of this policy [21].

$$\nabla J(\theta) \propto \sum_s \mu(s) \sum_a q_\pi(s,a) \nabla \pi(a|s,\theta) \tag{2.12}$$

$$= E_\pi \Big[\sum_a q_\pi(S_t,a) \nabla \pi(a|S_t,\theta) \Big] \tag{2.13}$$

2.7. State of Art

2.7.1. Dexnet

2.7.2. DQL Google

3. Simulator Choice

Simulator choice was the first important architecture decision we made, because it influences the whole software architecture. Simulator lays the groundwork of the robotics environment implementation. Especially for continuous control optimization tasks, accurate simulation plays a significant role in the performance of the controller. As Todorov et al. indicated, if the simulation is not accurate enough, an optimization algorithm will find a way to exploit it [24]. We compared three states of art simulators: Mujoco[1], Gazebo[2], and Pybullet[3]. Each simulator comes with advantages and drawbacks. Our decision is based on the factors: active support, community, stability, scalability, and ease of use. It is important to note that our analysis includes subjective factors such as ease of use, documentation coverage, and tutorials quality. Although we tried our best to ground our points on facts, subjective criteria include a certain amount of personal preferences.

3.0.1. Mujoco

Mujoco is released in 2015, making it the newest physics engine in our comparison. It stands for Multi-Joint Control. Hence the name, its primary purpose is Robot simulation.

We first considered Mujoco as our main simulator. Our consideration was based on; Roboticist mainly using Mujoco at OpenAI and DeepMind [25]. In addition, simulation engine reviews featured Mujoco as the best performing and stable engine [26]. Erez et al. conducted tests that compared the performance of physics engines on grasping tasks, where Mujoco by far performed better than the other engines 3.1. Additionally, Mujoco provides an API that lets users develop in C language. C language API is a significant advantage for researchers aim to get as close to the hardware as possible to save time. Another plus is mujoco-py offers a Python API to control Mujoco simulation easily. OpenAI product Mujoco-py[4] is entirely open-source with MIT license.

On the other hand, MuJoCo requires a license to use for research purposes. Personal non-commercial license costs 500$ as of 2020 July. License cost is the main drawback because we prefer complete open-source software. Another factor is the training time since our models require over 10M time-steps to train, we need to make use of every millisecond time gain in every step. So, GPU support is highly crucial. Mujoco only supports CPU simulation, which has the potential to be slower than GPU. As a side-note,

[1] `http://www.mujoco.org/`
[2] `http://gazebosim.org/`
[3] `https://pybullet.org/`
[4] `https://github.com/openai/mujoco-py`

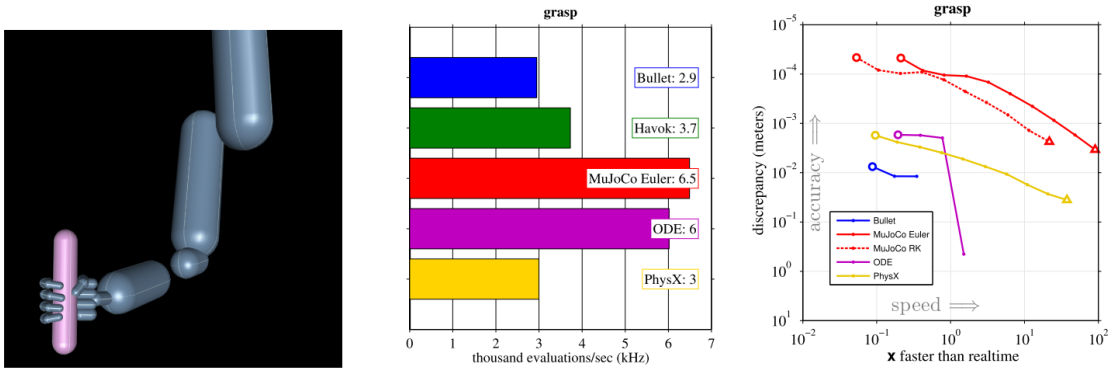


Figure 3.1.: physics engine performance on grasping task. Mujoco performs the best [26]

we have not compared the MuJoCo CPU version speed with Bullet GPU version speed. MuJoCo developers prepared a performance page where they explain the GPU vs. CPU comparison. They pointed out that if decoupled systems are to be simulated like particle simulation, GPU has an advantage. Whereas, one simulates coupled system such as a humanoid robot CPU gain a slight edge 3.2. They also noted that there is room for research in the areas besides coupled or decoupled systems[5].

Finally, observing large open-source projects like OpenAI-Roboschool, which initially used MuJoCo, deprecating, and suggesting PyBullet, made us reconsider. We believe that the reason community migrating towards PyBullet is completely open-source codebase.

3.0.2. Gazebo

The Gazebo is the oldest simulator among Bullet and Mujoco. The development of Gazebo dates back to the 2002 University of Southern California. Later, Willow Garage took over action and extended Gazebo to ROS and PR2. Gazebo became the primary simulation engine of the ROS community. Eventually, in 2012 Gazebo became part of OSRF(Open Source Robotics Foundation)[6], a spin-off from Willow Garage.

Technically, Gazebo is a simulation platform, which inherits different physics engines, such as Bullet, ODE[7], Simbody[8], and DART[9]. According to the documentation of Gazebo 11.0, it supports ODE engine default, and other engines can be used, if developers compile Gazebo from the source. That means the performance of the overall Gazebo simulation highly depends on those individual physics engine's performances. Another dependency of Gazebo is ROS(Robotics Operating System)[10]. ROS infrastructure handles all communication. Thus, users need to rely on ROS to interact with Gazebo. We believe

[5] http://mujoco.org/performance.html
[6] https://www.openrobotics.org/
[7] https://www.ode.org/
[8] https://simtk.org/
[9] https://dartsim.github.io/
[10] https://www.ros.org/

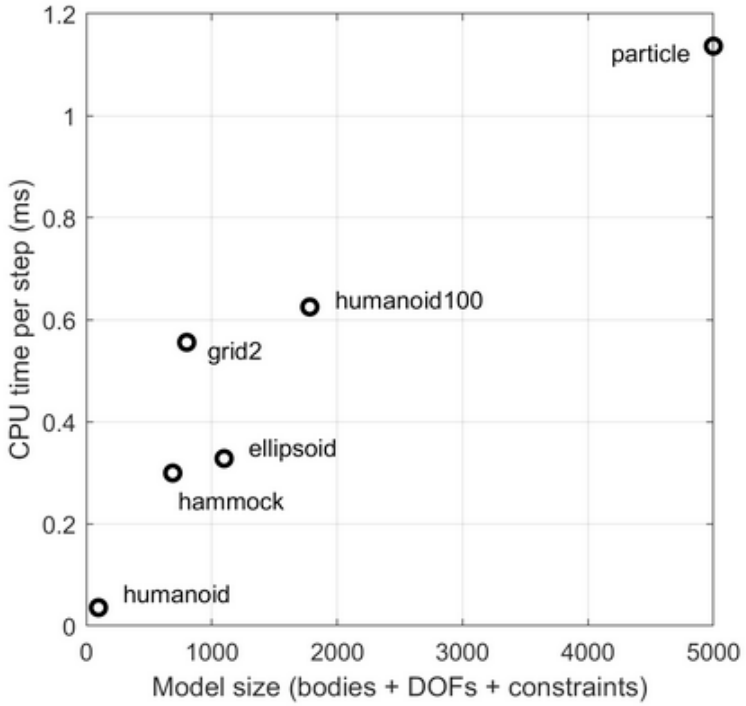


Figure 3.2.: CPU time per step comparison of different tasks [26]

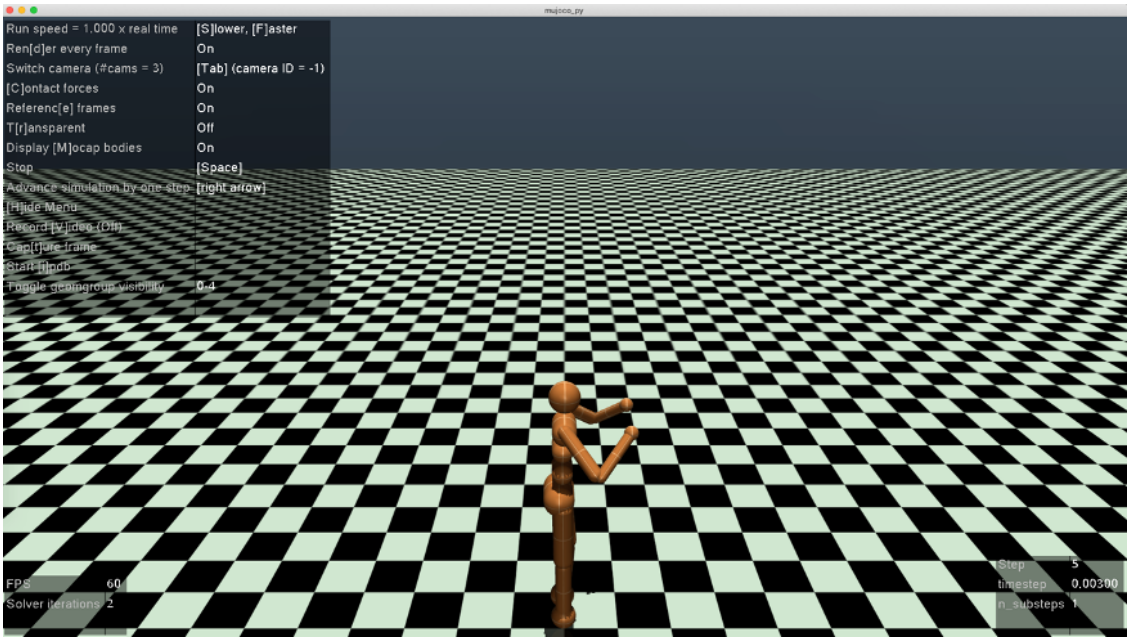
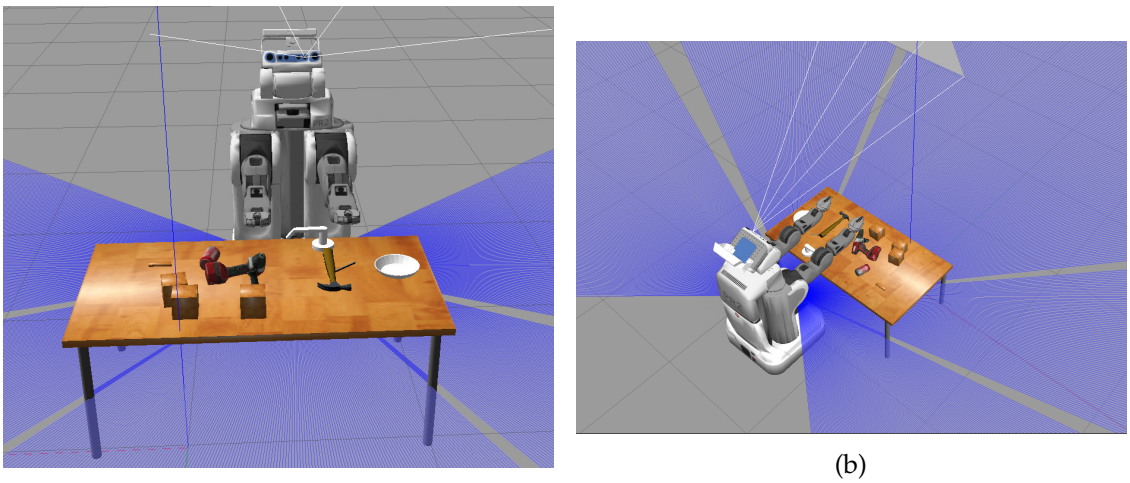


Figure 3.3.: Mujoco simulation of a humanoid model. Rendered with MJViewer



(a) (b)

Figure 3.4.: Table-top environment in Gazebo simulation with variety of objects and PR2 robot

this assumption is too large. Even if relying on ROS can bring a lot of well-structured tool with it, learning ROS has a steep learning curve and has the potential to cause a large overhead for simple projects. Nonetheless, developers invested highly on neat and clean documentation to reduce the overhead for new users. We consider the documentation and tutorials as a merit of the open-source project. Correspondingly, being open source contributes hugely to a large community willing to support, answering questions on forums, and submitting pull requests for possible bug fixes.

According to Pitonakova et al., Gazebo has usability issues due to not having a 3D mesh editing option and difficulties of installing dependencies for 3rd party models. They also noted that Gazebo performs fairly well in large simulation environments, so it could be more convenient to conduct extensive swarm robotics experiments on Gazebo [27].

Based on our experiments in 3.4, we found that Gazebo provides useful models to easily setup a table-top environment for robotics picking applications. Although we have not performed any grasping experiments on Gazebo, being able to edit the size, position, and orientation of models directly on simulation GUI is a useful feature, which lacks both on Pybullet and Mujoco.

3.0.3. PyBullet

PyBullet is a simulator built on the Bullet physics engine. Bullet's initial release dates back to 2006. Bullet engine was initially game, and graphics focused, but lately, with PyBullet, it has been increasingly popular among roboticists. We decided on using PyBullet for several strong reasons and overall satisfied by the performance and the features it offers. Firstly, PyBullet recently published their RL resources on Github

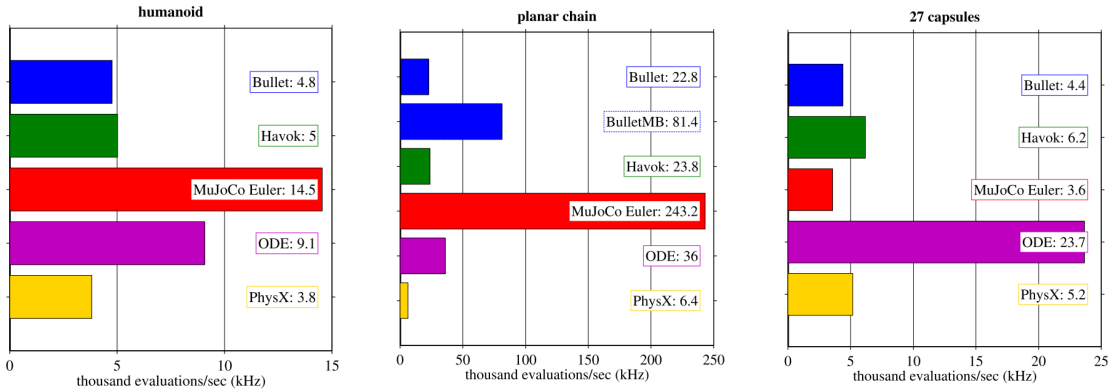


Figure 3.5.: Comparing physics engine performances. Bullet is either at the last place or the one above the last position [26]

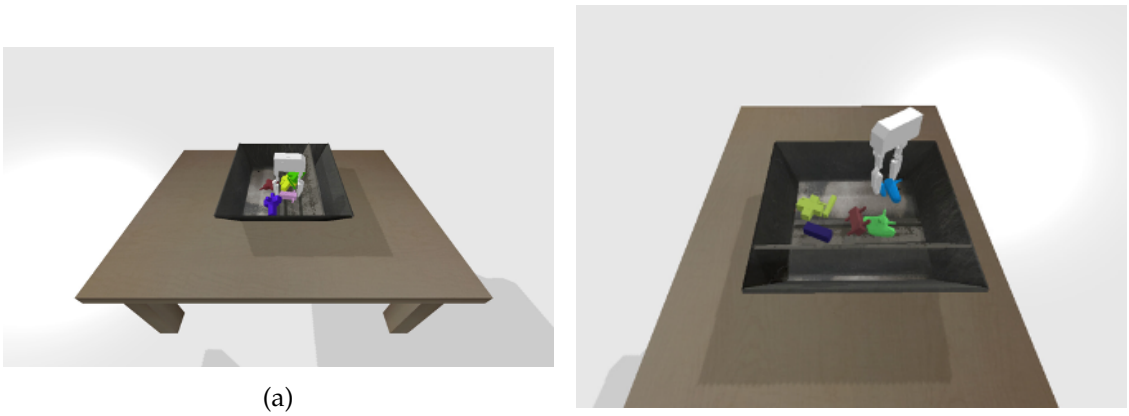
[**RLBullet**]. These resources provide everything necessary to quickly start experimenting with any choice of robot, environment, and algorithm. Secondly, our reference papers, in the area of RL robotics research, are using PyBullet for their experiments [12] [13]. Therefore, it is more convenient to compare results by using the same physical engine to avoid simulation differences. Thirdly, it has sizeable open-source support and free to use.

On the other hand, based on Erez et al. performance tasks, which compares Bullet, Mujoco, ODE, and PhysX engines, Bullet is either at the last place or the one above the last position 3.5 figure. Similarly, they mention the incompatibility of Bullet Engine's spring-damper system with the standard PD controller design [26].

Many open-source robotics learning resources migrating to PyBullet. This migration brings more open-source contributors who are more focused on Reinforcement Learning. For example, open-source contributors recently developed multi-threading GPU support to PyBullet. Also, stable-baselines[11] creators implemented a RL training package under Bullet's Github repository[12] [2].

In conclusion, PyBullet is the most actively developed physics engine among three contenders. Thanks to the open-source community, any small bug is reported and solved in a short time, which is missing in Gazebo and Mujoco. We assume more roboticist will migrate to PyBullet in the future. Hereby, it will become primary physics engine for robotics research. Despite research papers represent Pybullet engine performance as the worst among three, in practice we have not noticed any significant failure related to engine performance.

[11] `https://github.com/hill-a/stable-baselines`
[12] `https://bit.ly/3jqU7Kd`



(a) (b)

Figure 3.6.: Screenshot from our trained hand model on Pybullet

Simulator	**Gazebo**	**MuJoCo**	**Pybullet**
Designed For	Robotics	Robotics	Graphics/Games/Robotics
License	Open-Source	Closed-Source	Open-Source
API	C++/Python	C	Python
Documentation	4/5	3/5	5/5
Ease of Use	2/5	3/5	5/5

Table 3.1.: Comparison of simulators. Finall, we decided on PyBullet based on given criteria

4. Reinforcement Learning Algorithms and Tools

In this chapter, we will dig deeper into Reinforcement Learning algorithms. How they algorithms are implemented, what are their strengths and weaknesses? We will present our state-of-art algorithm, SAC (Soft-Actor-Critic), and the algorithm we want to test on the robotics applications, BDQ (Branched-Dueling Q-learning). We will mention the fundamental differences between those two algorithms—for instance, their optimization objective functions, and different exploration approaches.

After the introduction of algorithms, we are going to present RL environment frameworks and algorithm libraries. We base our custom robotics environment on Gym environment definition. In the same way, we intensively used open-source RL baseline algorithm library called Stable-Baselines. For the implementation of neural networks, we imported Tensorflow and Keras. Finally, we introduce Optuna as our hyper-parameter optimization tool.

Overall we depend on a lot of different software libraries, which we don't mention here; the interested audience can take a look at our Github page[1].

4.1. Soft Actor Critic(SAC)

SAC algorithm is described as the state-of-art algorithm as of 2020 [2]. Therefore, we chose SAC as our baselines algorithm to compare the BDQ against. SAC is an actor-critic, model-free algorithm. Actor critic refers to the optimization of both policy and value function. Model-free nature stems from the update structure that works without any underlying model. The success of SAC lies in low sample complexity and robustness to different hyperparameters [28]. SAC achieved this success due to; actor-critic architecture, entropy maximization, and off policy update structure.

[(TODO: elaborate more on actor-critic)]

Actor-critic architectures have long been used in RL literature [29]. [28].The actor-critic concept has begun to be successfully applied to problems since neural networks and computational capability increased (FIND REFERENCE). The core idea behind the actor-critic is optimizing the policy and value functions separately but combining them during the policy iteration part of the RL algorithm. The policy function is responsible for the policy evaluation, while the value function is responsible for policy improvement.

[1] `https://bit.ly/3k8uSga`

This way, researchers harness both strengths of both worlds. Policy function

$$\pi^*_{MaxEnt} = \arg\max_{\pi} \sum_t \mathop{\mathbb{E}}_{(s_t,a_t)\sim\rho_\pi} [r(s_t,a_t) + \alpha H(\pi(.|s_t))] \tag{4.1}$$

$$H(X) = \mathop{\mathbb{E}}_{X}[I(x)] = -\sum_{x\in X} p(x)\log p(x) \tag{4.2}$$

Off policy, algorithms are naturally better at working in the sparse data region, because off-policy algorithms can incorporate past experiences or use state-action-rewards pairs from different policies. Albeit the off-policy approach brings high variance into the learning process, new papers overcome this problem with Polyak-Rupper averaging or adaptively setting the step size of the stochastic gradient descent optimizer [17].

4.1.1. SAC Implementation as Baseline Algorithm

We use the stable-baselines implementation of the SAC algorithm. This implementation uses double soft-Q functions and a soft-state value function to estimate the critic, and a policy network to estimate the actor. Stable baselines support automatically learning entropy coefficient or entropy. This feature saves the user time by avoiding hand-tuning on the entropy coefficient term.

Unlike the tabular soft-policy iteration method, where policy evaluation and policy iteration steps follow each other strictly, soft-actor-critic calculates the losses of both critic and actor update the parameters by stochastic gradient descent in one iteration. Although function approximator implementation of SAC doesn't directly follow the policy-iteration, it inherently follows the generalized policy iteration schema.

The essential characteristic of SAC is the entropy maximization. Entropy bonus comes into play when calculating the bellman backup of soft-Q-function, soft-state value function, and the policy loss. That means the learned policy must maximize the rewards and entropy at the same time.

The soft Q-function loss is represented in the equation below 4.5, which is the same loss function used by Mnih et al. in 2015, updates the parameters of the Q-network in the direction of the TD target. The only difference in the Q-function update step between SAC and DQN is the inclusion of entropy variable in the state-value network 4.3.

$$V(s_t) = \mathop{\mathbb{E}}_{a_t\sim\pi}[Q(s_t,a_t) - \alpha\log\pi(a_t|s_t)] \tag{4.3}$$

$$\pi_{new} = \arg\min_{\pi'\in\Pi}\left(\pi'(.|s_t)\middle|\middle|\frac{exp(\frac{1}{\alpha}Q^{\pi_{old}}(s_t,.))}{Z^{\pi_{old}}(s_t)}\right) \tag{4.4}$$

$$J_Q(\theta) = \mathop{\mathbb{E}}_{(s_t,a_t)\sim D}\left[\frac{1}{2}(Q_\theta(s_t,a_t) - (r(s_t,a_t) + \gamma \mathop{\mathbb{E}}_{(s_t,a_t)\sim p}[V_{\theta^-}(s_{t+1})]))^2\right] \tag{4.5}$$

SAC and DQN diverge in the policy improvement step, where DQN updates the policy based-on epsilon-greedy approach, SAC parameterizes the policy with neural network and updates the parameters in the direction of the minimum loss function 4.6. Haarnoja et al. manipulate the policy definition with a reparameterization trick to allow stochastic descent on the loss function 4.7.

$$J_\pi(\phi) = \underset{s_t \sim D, \epsilon \sim N}{\mathbb{E}} \Big[\alpha \log \pi_\phi(f_\phi(\epsilon_t; s_t)|s_t) - Q_\theta(s_t, f_\phi(\epsilon_t; s_t)) \Big] \tag{4.6}$$

$$a_t = f_\phi(\epsilon_t; s_t) \tag{4.7}$$

The soft Actor-Critic algorithm given in 4.1 follows the general guidelines of actor-critic type of algorithms with the introduction of entropy maximation RL into the definitions of Q and policy functions.

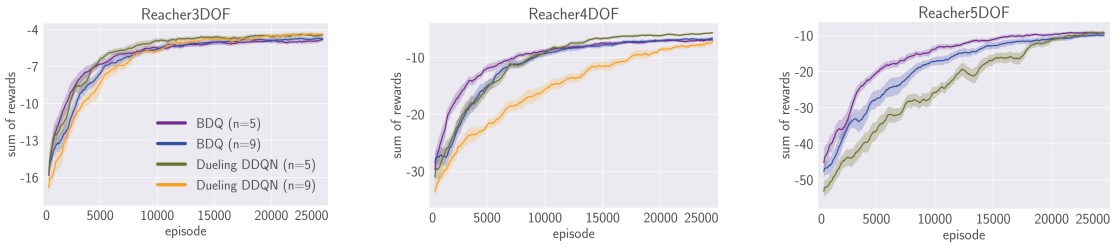
Algorithm 1 Soft Actor-Critic

Input: θ_1, θ_2, ϕ ▷ Initial parameters
  $\bar{\theta}_1 \leftarrow \theta_1, \bar{\theta}_2 \leftarrow \theta_2$ ▷ Initialize target network weights
  $\mathcal{D} \leftarrow \emptyset$ ▷ Initialize an empty replay pool
  for each iteration **do**
    for each environment step **do**
      $\mathbf{a}_t \sim \pi_\phi(\mathbf{a}_t|\mathbf{s}_t)$ ▷ Sample action from the policy
      $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$ ▷ Sample transition from the environment
      $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}_t, \mathbf{a}_t, r(\mathbf{s}_t, \mathbf{a}_t), \mathbf{s}_{t+1})\}$ ▷ Store the transition in the replay pool
    end for
    for each gradient step **do**
      $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$ ▷ Update the Q-function parameters
      $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$ ▷ Update policy weights
      $\alpha \leftarrow \alpha - \lambda \hat{\nabla}_\alpha J(\alpha)$ ▷ Adjust temperature
      $\bar{\theta}_i \leftarrow \tau\theta_i + (1-\tau)\bar{\theta}_i$ for $i \in \{1, 2\}$ ▷ Update target network weights
    end for
  end for
Output: θ_1, θ_2, ϕ ▷ Optimized parameters

Figure 4.1.: SAC pseudocode [28]

4.2. Branching Dueling Q-Network (BDQ)

BDQ is our test algorithm. Tavakoli et al. developed BDQ as a variant of Dueling Double DQN [30]. They aimed to solve the intractability of the DQN algorithm on high dimensional continuous tasks. The key feature of their algorithm is the shared module. The shared module representation allowed the DQN algorithm to cope with the intractability problem. Tavakoli et al. showed that their network could output multi-dimensional actions without convergence issues. They believe the stability of the structure is due to the encoded latent representation of the input in the shared module.



(a) (b) (c)

Figure 4.2.: BDQ performances compared to Dueling-Double-DQN on increasing action spaces

Their results stress that, especially in higher dimensional action spaces, BDQ performs better than Double-dueling DQN implementation 4.2. Even compared to proven algorithms, like DDPG, it cannot reach the level of BDQ. Although researchers at google deep mind presented in 2016 that the DDPG algorithm outperforms DQN variants at almost every task [31], Tavakoli et al. proved the opposite that BDQ shows better performance than DDPG on Humanoid walking benchmark task 4.3.

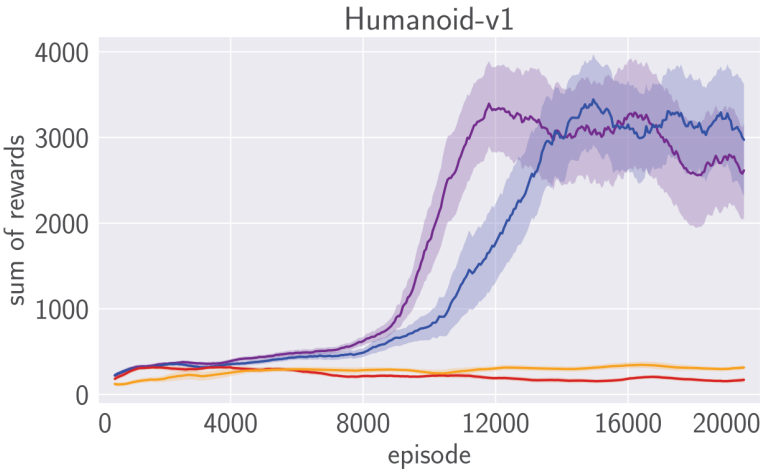


Figure 4.3.: Blue line represents

In this section, we will go through the implementation details of BDQ. The authors of the BDQ article provided their implementation of BDQ on Github. Based on the original code and the insights from the article, we implemented our version of BDQ on stable-baselines codebase. As a result, we avoid the save, load model issues from BDQ original code, and use new features available such as callback structure, parameter manipulation, warn starting, etc.

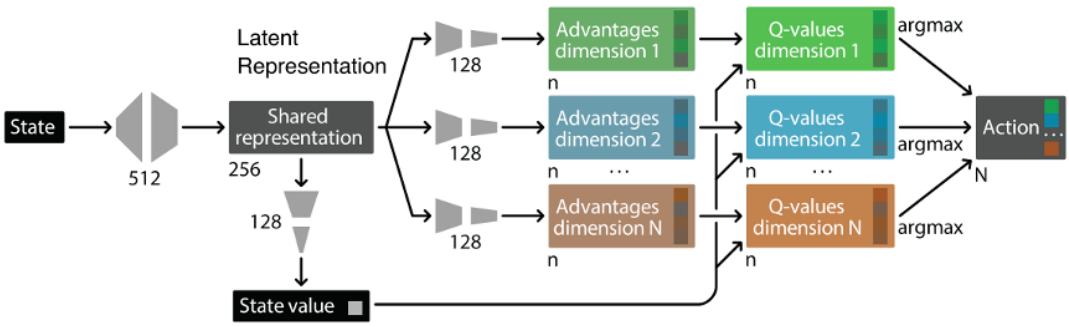


Figure 4.4.: BDQ network representation

4.2.1. BDQ Implementation

BDQ adopts new improvements from the DQN algorithm, such as double-q function, dueling architecture, prioritized replay. One crucial design decision is they choose to keep the same state-value estimation for each action branch, while advantage functions are unique to every stream of actions 4.4. Later they combine common state-value estimate and advantage function in the aggregation layer. This approach helps with the generalization of the actions in similar states by reducing the overfitting of action branches. Therefore, they can scale up to more complex and higher dimensional tasks, where Dueling-Double DQN becomes intractable.

Another key difference of BDQ is the aggregation layer; they subtract the mean advantage value from the advantage value of an individual branch. Then, sum up the result to calculate the Q-function value of each branch **??**. Although the lack of identifiability problem, they achieve better results than the theoretically proven max reduction method 4.9.

$$Q_d(s, a_d) = V(s) + \left(A_d(s, a_d) - \frac{1}{n} \sum_{a'_d \in A_d} A_d(s, a'_d)\right) \tag{4.8}$$

$$Q_d(s, a_d) = V(s) + \left(A_d(s, a_d) - \max_{a'_d \in A_d} A_d(s, a'_d)\right) \tag{4.9}$$

TD-target definition of BDQ also differs from DDQN. Where DDQN based approach calculates the individual TD-target for every branch 4.10, BDQ sets one global target for all actions by taking the mean of the max Q-function variable in the TD-target equation 4.11. In our opinion, a common TD-target for all branches of BDQ underlines the dependency between action branches and forces them to act in collaboration.

$$y_d = r + \gamma Q_d^- \left(s', \arg\max_{a'_d \in A_d} Q_d(s', a'_d)\right) \tag{4.10}$$

$$y = r + \gamma \frac{1}{N} \sum_d Q_d^- \left(s', \arg\max_{a'_d \in A_d} Q_d(s', a'_d)\right) \tag{4.11}$$

Analogous to the TD-target definition, they express loss differently than the DDQN counterpart. BDQ authors calculate the loss first by taking the mean of the squared TD-error over the branches and then taking the expectation of this score 4.12. Identical to the TD-target calculation, loss definition also helps the action branches to act dependent on each other.

$$L = \mathop{\mathbb{E}}_{(s,a,r,s')\sim D}\Big[\frac{1}{N}\sum_{d}(y_d - Q_d(s,a_d))^2\Big] \tag{4.12}$$

Exploration-exploitation trade-off is still on-going research in RL. Nevertheless, researchers assume better-exploring algorithms have the edge over weakly exploring algorithms, such as SAC with a robust entropy-based exploration approach is considered the best exploring algorithm and the state-of-art RL algorithm [28]. BDQ original code offers two different exploration approach, epsilon greedy and gaussian noise. Since epsilon-greedy usually used with discrete DQN based algorithms, the authors found it inadequate to explore continuous spaces. Instead of epsilon-greedy, they recommended the use of Gaussian-noise for better performance.

BDQ follows the same pseudocode of double-DQN(4.5) with dueling and branching network extensions, which does not affect the underlying algorithm.

Algorithm 1: Double DQN Algorithm.

input : $\mathcal{D}$ – empty replay buffer; θ – initial network parameters, θ^- – copy of θ
input : N_r – replay buffer maximum size; N_b – training batch size; N^- – target network replacement freq.
for *episode* $e \in \{1, 2, \ldots, M\}$ **do**
  Initialize frame sequence $\mathbf{x} \leftarrow ()$
  for $t \in \{0, 1, \ldots\}$ **do**
    Set state $s \leftarrow \mathbf{x}$, sample action $a \sim \pi_{\mathcal{B}}$
    Sample next frame x^t from environment $\mathcal{E}$ given (s, a) and receive reward r, and append x^t to $\mathbf{x}$
    if $|\mathbf{x}| > N_f$ **then** delete oldest frame $x_{t_{min}}$ from $\mathbf{x}$ **end**
    Set $s' \leftarrow \mathbf{x}$, and add transition tuple (s, a, r, s') to $\mathcal{D}$,
      replacing the oldest tuple if $|\mathcal{D}| \geq N_r$
    Sample a minibatch of N_b tuples $(s, a, r, s') \sim \text{Unif}(\mathcal{D})$
    Construct target values, one for each of the N_b tuples:
    Define $a^{\max}(s'; \theta) = \arg\max_{a'} Q(s', a'; \theta)$
    $y_j = \begin{cases} r & \text{if } s' \text{ is terminal} \\ r + \gamma Q(s', a^{\max}(s'; \theta); \theta^-), & \text{otherwise.} \end{cases}$
    Do a gradient descent step with loss $\|y_j - Q(s, a; \theta)\|^2$
    Replace target parameters $\theta^- \leftarrow \theta$ every N^- steps
  end
end

Figure 4.5.: Double-DQN pseudocode [32]

4.3. OpenAI Gym

The gym framework provides a standard definition of a reinforcement learning environment. It assumes that every environment is formalized with the Markov Decision Process (defined in section-2.3.2) [25]. Hence, it follows the structure of the agent taking action and receiving observation and reward as a result of it.

```
ob0 = env.reset() # sample environment state, return first observation
a0 = agent.act(ob0) # agent chooses first action
ob1, rew0, done0, info0 = env.step(a0) # environment returns observation,
# reward, and boolean flag indicating if the episode is complete.
a1 = agent.act(ob1)
ob2, rew1, done1, info1 = env.step(a1)
...
a99 = agent.act(o99)
ob100, rew99, done99, info2 = env.step(a99)
# done99 == True  =>  terminal
```

Figure 4.6.: Gym interface to interact with an environment

The code example 4.6 demonstrates, the interaction between an agent and the environment. OpenAI designed the Gym framework in a way it is agent diagnostic. Therefore, it allows the user to try different algorithms on the agent side freely. The environment, on the other hand, should follow the Gym guidelines. A custom gym environment has to override the step, reset, seed, render, and close. Step function runs one timestep of the environment and returns a tuple of reward, observation, done, and info. Reset function resets the domain setting to a random or predefined initial state and returns the observation of that state. Seed function starts the seeding of the random number generator. Close function is called at the end when the user wishes to quit the environment. Thus, it performs the necessary memory clean-up or resource deallocation.

Listing 4.1: Gym environment example instantiation

```
from gym.envs.registration import register

register(
    id='gripper-env-v0',
    entry_point='manipulation_main.gripperEnv.robot:RobotEnv',
)

env = gym.make('gripper-env-v0', config='config/gripper_grasp.yaml')
```

Gym environment definition also provides a useful helper gym.make function. After the registration of the custom environment, one can instantiate the environment with a simple one-liner represented in the code 4.1. It also allows the user to pass an argument to the constructor of the custom environment. In our case, we provide the configuration file as an argument.

4.4. Stable Baselines

While the OpenAI gym framework identifies the environment, Stable Baselines provide the agent part of the RL framework. Stable Baselines is a powerful open-source fork of OpenAI baselines. Yet it is based on OpenAI Baselines; it has surpassed the performance

of OpenAI Baselines in many ways. The authors of Stable Baselines have composed a Medium article[2] that describes every additional feature and bug fix over OpenAI baselines. In this section, we will only mention the critical components needed for our project.

First and foremost, Stable Baselines has strong support for the state-of-art algorithm SAC. SAC proved to be the best algorithm we tested on our environment. Apart from SAC, it support 10 more algorithms[3]. Stable Baselines maintains a sophisticated save/load structure. Since, we aim to warm-start and fine-tune the neural network variables, we should be able to save and load the network variables individually. A use-case in our application is truncating the last soft-max layer of a saved model to change the action-space size. We often encountered problems with OpenAI Baselines save/load structure.

Moreover, Stable Baselines supports input and reward normalization. Later in the result part, we will show our best performing model is equipped with both input and reward normalization.

Lastly, because of the extra features, fully documented and tested code-base, we decided to reimplement BDQ algorithm on Stable Baselines. Example of how to run a simple training and saving can be seen below in 4.2

Listing 4.2: Example of training and saving BDQ algorithm on gripper-env

```
import gym

from stable_baselines.bdq.policies import MlpActPolicy
from stable_baselines import BDQ

env = gym.make('gripper-env-v0', config='config/gripper_grasp.yaml')

model = BDQ(MlpActPolicy, env, verbose=1)
model.learn(total_timesteps=10000)

obs = env.reset()
for i in range(1000):
    action = model.predict(obs)
    obs, rewards, dones, info = env.step(action)

env.close()
```

[2] https://bit.ly/3ia3GvM
[3] a2c, acer, acktr, ddpg, dqn, gail, her, ppo, trpo, td3

4.5. Machine Learning Framework

RL owes its success partly to a strong function approximator, deep neural networks. Where, tabular Q-function only solved games like tic-tac-toe, neural networks integration to Q-function solves high dimensional complex tasks like Atari games [22]. The growing success of neural networks inspired large companies like Google and Facebook to start their own open-source machine learning frameworks. Among those projects, Tensorflow, Keras, and PyTorch are the most popular ones [33] [34] [35].

Granted that we decided to work with Tensorflow and Keras on different parts of the project, it is worth mentioning that PyTorch is becoming dominant in research [36]. In the figure 4.7 demonstrates how Pytorch has risen steeply in terms of mentions in the major conferences. It achieved a staggering comeback from a maximum 6% mentions to 78.72% mentions in 3 years.

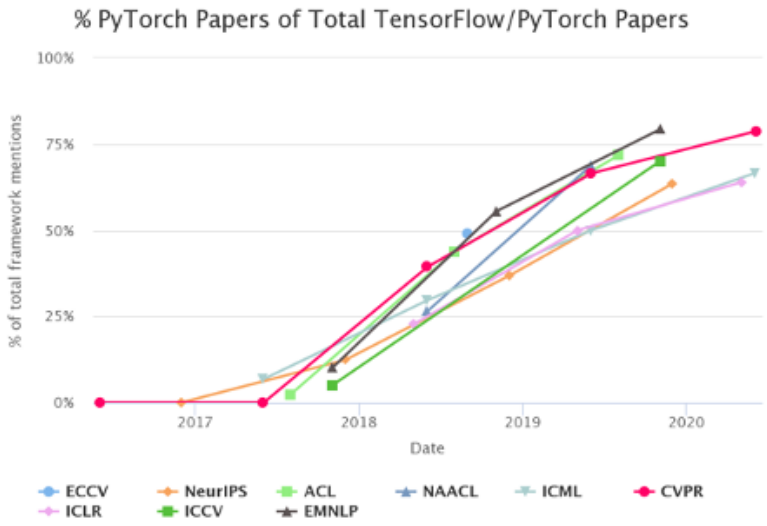


Figure 4.7.: PyTorch and Tensorflow comparison based on the mentions in major machine learning conferences [36]

According to the researchers, PyTorch's success is due to simplicity, great API, and Performance. Even Tensorflow, in its last edition Eager, delivered a similar API to PyTorch. Yet there have been reports about the weaknesses of Eager in performance and memory. In short, it is unlikely that Tensorflow recovers and catches PyTorch anytime soon.

In conclusion, it is also possible to see the transition from Tensorflow to Pytorch in the RL community as well. Stable Baselines released the PyTorch version of Baselines algorithms in May 2020 [37]. OpenAI Spinningup, which is an educational incentive for RL teaching from OpenAI, has moved to PyTorch in February 2020. And now host the master branch with PyTorch implementation [21].

5. Curriculum Learning

One can gradually increase the level of the difficulty of a specific task to be learned to guide the training process and speed up the convergence time. Based on phycological studies, humans learn faster when they subject to the information in the form of a unique curriculum. That is because we are subjected to curriculum learning since they were toddlers.

6. Experimental Setup

6.1. Implementation

6.1.1. BDQ Algorighm Implementation

Object Recognition

6.1.2. Network Architecture

6.1.3. External Libraries

6.1.4. Testing Structure

6.1.5. Run the Code

6.2. Curriculum Integration

6.2.1. Curriculum Parameters

6.3. Hyperparameter Search

6.4. GPU vs. CPU

7. Evaluation

8. Conclusion & Future Work

8.1. Conclusion

8.2. Future Work

- Entropy maximization framework implementation of BDQ for better exploration
- Try with different perception approaches. Without autoencoder directly passing the image to CNN
- Transfering the models learned in simulation to real-world

A. General Addenda

If there are several additions you want to add, but they do not fit into the thesis itself, they belong here.

A.1. Detailed Addition

Even sections are possible, but usually only used for several elements in, e.g. tables, images, etc.

B. Figures

B.1. Example 1

✓

B.2. Example 2

✗

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