

# Model-free Deep Reinforcement Learning – Algorithms and Applications

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**Abstract** Insert your abstract here. Include keywords, PACS and mathematical subject classification numbers as needed.

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### 1 Introduction

Artificial neural networks have been used in machine learning since the beginning. The first steps towards today's neural networks can be dated back to McCulloch and Pitts [28], who wrote about how neurons might work and created the first electrical circuits based on this idea. The following advancements of computers provided a boost to neural networks, e.g. the Dartmouth Summer Research Project on Artificial Intelligence [27]. In the following years, Rosenblatt invented the Perceptron completely build in hardware [39]. Minsky and Papert followed up on this and wrote in their book *Perceptrons* [29] that Rosenblatt's perceptron is not able to learn more complex behavior such as XOR problems. This led to researchers mostly abandoning neural networks until MADALINE [58] was able to solve a real world problem. Due to the lack of computational resources, the excitement decayed shortly after. More recently, the advancements of computers allow to compute neural networks efficiently. This has shown great success in e.g. computer vision [20, 13], but also found applications in reinforcement learning, such as the game of Go [46], Dota 2 [34] or for the Atari Games [32]. Based on this success, this survey provides an overview of the current model-free reinforcement learning algorithm landscape and presents some popular application examples.

### 2 Background

A Markov Decision Process (MDP) is defined as a tuple  $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R})$ , where  $\mathcal{S}$  is a finite set of states,  $\mathcal{A}$  is a finite set of actions and  $\mathcal{T} : \mathcal{S} \times \mathcal{A} \rightarrow \Pi(\mathcal{S})$  represents

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the state transition function, which returns a probability distribution over states.  $\mathcal{R} : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$  returns the expected immediate reward for taking each action in each state. This paper mainly considers the infinite horizon MDP, which tries to maximize the expected discounted cumulative reward:

$$G_t = \mathbb{E} \left[ \sum_{\tau=t}^{\infty} \gamma^{\tau-t} \mathcal{R}(s_{\tau}, a_{\tau}) \middle| s_t, a_t \right]$$

Here  $\gamma \in [0, 1)$  describes the discount factor, which trades off immediate and future rewards. Reinforcement learning algorithms now aim to find a policy  $\pi : \mathcal{S} \rightarrow \mathcal{A}$ , which describes the optimal behavior to maximize the expected future reward from all states. Consequently, an action-value function, which returns the value of taking an action  $a$  in state  $s$ , under the policy  $\pi$  is defined as:

$$Q_{\pi}(s, a) = \mathbb{E}[G_t | s_t = s, a_t = a, \pi] = \mathcal{R}(s, a) + \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s, a, s') \max_{a'} Q_{\pi}(s', a')$$

In order to find the best policy, value-based methods are interested in finding the optimal action-value function  $Q^*(s, a) = \max_{\pi} Q_{\pi}(s, a)$ , which is equivalent to finding the optimal policy

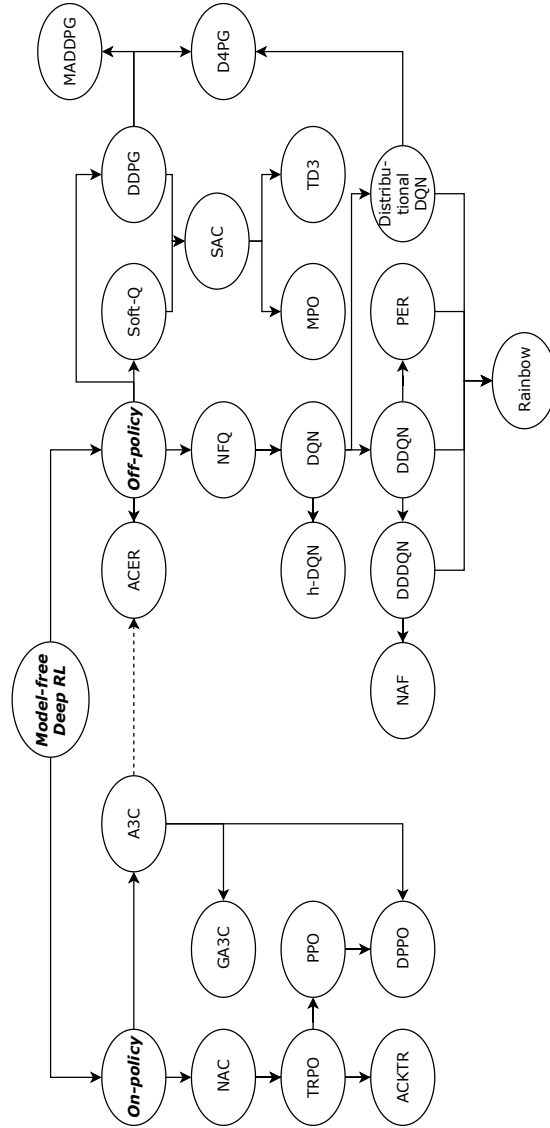
$$\pi^*(s) = \arg \max_a \mathcal{R}(s, a) + \gamma \sum_{s' \in \mathcal{S}} \mathcal{T}(s, a, s') \max_{a'} Q^*(s', a')$$

Alternatively, the optimal value function  $V^*(s) = \mathbb{E}[G_t | s_t = s, \pi] = \max_a Q^*(s, a)$  can be used.

In contrast to value-based methods, policy-based methods directly parameterize a policy  $\pi(s; \theta)$ . One such method is REINFORCE [57], it updates the policy parameters  $\theta$  in the direction  $\nabla_{\theta} \mathbb{E}[G_t] \approx \nabla_{\theta} \log \pi(s_t; \theta) G_t$ . In order to reduce variance and keep the estimate unbiased, a baseline  $b(s_t)$  is subtracted from the return  $\nabla_{\theta} \log \pi(s; \theta) (G_t - b(s_t))$ . For this baseline, it is common to use an estimate of the value function  $b(s_t) \approx V_{\pi}(s_t)$ . By applying the policy gradient theorem,  $G_t - b(s_t)$  can be seen as an estimate of the advantage function  $A_{\pi}(s_t, a_t) = Q_{\pi}(s_t, a_t) - V_{\pi}(s_t)$ . Combining parameterized policies and value function estimator results in *actor-critic* (AC) methods.

### 3 Algorithms

This section provides an overview of the current deep reinforcement learning landscape including improvements and state-of-the-art (Figure 3). Algorithms are classified as on-policy or off-policy. On-policy algorithms estimate the value of the policy while using it for control. In contrast, off-policy algorithms possess a generating policy, called *behavior policy*, and a *target policy*. The behavior policy is not necessarily related to the target policy, which is improved and evaluated. This allows to use a deterministic target policy, while sampling actions through a stochastic behavior policy. [51, chapter 5]



**Fig. 1** Overview of model-free reinforcement learning algorithms.

### 3.1 Off-Policy

Many current off-policy algorithms are based on the original *Neural Fitted Q-Iteration* (NFQ) [37] published in 2005. NFQ is based on vanilla Q-Learning [56] and approximates the action-value function with a multilayer-perceptron. Compared to other approaches at the time, NFQ allows to learn with relatively good data efficiency. Further, batches from a replay memory [23] are used in order to train the multilayer-perceptron with *resilient backpropagation* (RPROP) [38]. Thereby, it is possible to dynamically add new samples to the replay memory

during learning. Motivated by this idea as well as the success of TD-gammon [52] one of the biggest improvements in deep reinforcement learning, *Deep Q-Networks* (DQN) [32] were introduced. They built upon their prior results [31] on the Atari Arcade Environment [5] which already achieved state-of-the-art performance for some of the games. DQN introduces better scalability to larger data sets by replacing NFQ’s RPROP with *Stochastic Gradient Descent* (SGD) updates. Further, they allow training end-to-end from the raw visual input utilizing *convolutional neural networks* (CNN). Benchmarks of the more recent DQN version [32] show an improved performance as well as a better generalization to more Atari games compared to the initial work [31]. The performance improvement was mainly achieved by introducing a second target Q-network, which is only periodically updated and thereby reduces sample correlations. Despite the success, van Hasselt, et al. [12] show that DQNs are not sufficient to avoid overestimation of action-values under certain conditions. This in itself is not harmful to the policy’s performance, but if the overestimation is not uniform and not concentrated at the states of interest, it might affect the policy negatively. To mitigate the risk of overestimation, they propose *Double DQN* (DDQN). Double Q-Learning [11] in general tries to decouple the selection and evaluation of actions by learning two action-value functions. One determines the greedy policy and the other the value of this policy. In order to reduce the computational cost, DDQN utilizes the already existing online Q-network for determining the greedy policy and the target Q-network for estimating its value. Further, this allows to achieve better performance on most of the Atari games. Decoupling is also done in a more extreme form with *Dueling Double DQNs* (DDDQN) [55]. They represent the action-value by two separate function approximations, a state-value and a state-dependent action-advantage function estimate. This representation allows the dueling architecture to learn about the value of a state regardless of the action taken. This is especially important when the action has no repercussions about the near future. Combining DDQN with gradient clipping and *Prioritized Experience Replay* (PER) [40] shows that sampling rare experiences with a higher probability makes learning with replay memories more efficient. However, sampling non-uniformly from the replay memory introduces a bias, that has to be corrected during the update step. C51 [4] presents a distributional perspective to DQN. Instead of the expected future reward, i.e. action-value function, the corresponding distribution is computed. This allows to reduce chattering and provides a more stable training as well as a rich set of auxiliary predictions. A general comparison of different DQN version is presented by Hessel, et al. [15], they also introduce *Rainbow* combining different DQN improvements in one algorithm.

All previous approaches are using environments, which do not have to deal with delayed and sparse feedback. In real world applications this is often not the case and algorithms still need the ability to learn. One key problem, which occurs during training, is insufficient exploration, causing unstable policies. Using intrinsically motivated agents, exploration can be achieved through the agent itself rather than through an external goal. This idea is implemented by *hierarchical-DQN* (h-DQN) [21]. A top level meta-controller is selecting a subgoal in order to optimize the extrinsic reward. The lower level controller maximizes an intrinsic reward by solving the subgoal. This allows h-DQN to achieve a significant better performance on the Atari game Montezuma’s Revenge. In addition to that, real systems require to be able to work with continuous actions spaces and ensure sample complexity is low,

due to more costly data collection from e.g. robots. *Normalized Advantage Functions* (NAF) [8] address both problems with a DQN based algorithm. Similar to DDDQN, the Q-network is represented by one state-value function output and one state-dependent action-advantage function. In order to reduce sample complexity, NAF incorporates imagination rollouts. Those synthetic on-policy samples are created by utilizing a mixture of *iterative LQG* (iLQG) [53] and on-policy trajectories for real world rollouts. Afterwards, the learned model for the states is used to generate replay memory entries. This can be seen as a scalable variant of Dyna-Q [50]. As a drawback, NAF fails to show improvements using iLQG compared to on-policy samples, however, iLQG might be desirable when damage avoidance is crucial. Lillicrap, et al. [22] also adapt the underlying idea of DQN [32] and make it applicable to the continuous action domain. However, they do not follow an exclusively value-based learning method and introduce *Deep Deterministic Policy Gradients* (DDPG), an AC algorithm with approximate Q-Learning based on deterministic policy gradients (DPG) [47]. DQN’s architecture is improved by adding batch normalization layers [17] to deal with different physical units in the observation space. In order to stabilize policies, they adapt the idea of target networks from DQN and use soft target updates for AC. Following up on this, Haaranaja, et al. criticize that DDPG is brittle to hyper-parameter choices and the policy stability is difficult to achieve, consequently they present *Soft Actor Critic* (SAC) [10]. SAC is an improvement from *Soft-Q-Learning* (Soft-Q) [9], which combines the idea of Q-Learning with maximum entropy reinforcement learning. The soft action-value function allows the policy to represent complex multi-modal behavior and provides a natural exploration without adding additional noise. SAC avoids the complexity and potential instability of Soft-Q and forms a bridge between DDPG and stochastic policies by maximum entropy reinforcement learning. Similarly to NAF, they also approach the problem of sample efficiency and gain significant improvements compared to DDPG and several on-policy methods. In general they also found modeling the state-value function and the action-value function with two separate neural networks improved the stability of SAC. *Twin delayed DDPG* (TD3) [6] was developed in parallel to SAC and continues to address the hyperparameter sensitivity, but further shows that overestimation of the action-value function is also a pressing issue for AC methods. However, for the continuous actions space the approach of DDQN [12] is not easily applicable. Therefore, TD3 proposes three key improvements. A clipped variant of double Q-Learning trains two separate Q-Networks in order to reduce the overestimation bias. Policy smoothing, similar to expected SARSA [44], adds noise to the target action, which avoids exploiting action-value function errors and brings action-values of similar actions closer together. The most important improvement are delayed updates, i.e. the policy network as well as the target networks are updated less frequently than the Q-network. This reduces the risk of optimizing the policy based on incorrect value estimates and hence the policy is less likely to diverge. Building upon the idea of entropy reinforcement learning from SAC, *Maximum a-Posteriori policy optimization* (MPO) [1] transforms the RL problem in an inference problem, which allows them to utilize expectation maximization (EM) for training, while optimizing a relative-entropy objective. Similar to Rainbow, *Distributional Distributed DDPG* (D4PG) [3] combines different advancements with DDPG. This includes distributed actors, such as the on-policy *Asynchronous Advantage Actor Critic* (A3C) [30] and the distributional value estimate from C51. A3C also

has an off-policy counterpart *Actor-Critic with Experience Replay* (ACER) [54], which outperforms A3C by significant margin regarding performance and sample efficiency. This is achieved by Retrace [33] Q-value estimation, which reduces the bias of policy gradient estimates, whereas truncated importance weights help to reduce variance. Additionally, maintaining a running average of past policies forces the new policy to stay close to this average. This is similar to computing the *Kullback-Leibler* (KL) in *trust region policy optimization* (TRPO) but is computationally more efficient.

The above algorithms used multiple agents to provide better exploration and faster convergence, however the goal was to find the optimal policy for one worker. *Multi-agent DDPG* (MADDPG) [24] on the other hand is interested in using multiple agents to collaborate and/or compete. The decentralized actors are only trained with local information, which allows for easier inference, the centralized critics have access to all information during training. In order to reduce variance due to interactions with other actors, policy ensembles are proposed.

### 3.2 On-Policy

Comparably important to DQN in the on-policy setting is the introduction of *Asynchronous Advantage Actor Critic* (A3C) [30]. Besides A3C, Mnih, et al. also introduce asynchronous off-policy methods for Q-Learning and SARSA. However, they show that A3C outperforms the proposed off-policy methods. Multiple actor threads allow A3C to collect more experience in a larger space of the environment and incorporate it into one globally shared network. Consequently, the stability and robustness of the training process is increased without incorporating a replay memory. Further, less computational power is required to achieve better results compared to DQN. Similar to SAC entropy is included in objective function, however A3C utilizes it for regularization and not as constraint. Aside from the discrete Atari games, A3C was also tested for continuous action spaces and was able to learn reliable policies. GA3C combines A3C with GPU computation [2]. Following the concept of policy gradients, Schulman, et al. introduce *Trust Region Policy Optimization* (TRPO) [41]. TRPO can be seen as combination of minorization-maximization [16] and *Natural Actor Critic* (NAC) [35]. They criticize that first order gradient methods are often overconfident and not accurate enough in curved areas, which results in losing already made learning progress. Consequently, TRPO optimizes its policy by enforcing a trust region constraint. The trust region constraint represents a pessimistic/lower bound on the performance of the policy and guarantees monotonic improvement locally around the current policy. In order to be more computationally efficient, the natural policy gradient [19] is computed approximately with the *Conjugate Gradient* (CG) algorithm. Further, due to the multiple approximations, before applying the update, a backtracking line search determines whether the update still satisfies the KL constraint or not. One big drawback of TRPO in practice is its sample efficiency. Theoretically, TRPO can be applied to any policy, but it is often not practical to use deep neural networks policies. This shortcoming is addressed by *Proximal Policy Optimization* (PPO) [42]. PPO keeps all monotonic improvement guarantees while using first order optimization. This can be achieved in two ways. The KL constraint is replaced with KL regularization. Alternatively, the importance sampling weights

are clipped, which results in a lower bound for the unclipped objective. PPO can also be combined with A3C’s idea of distributed actors resulting into *Distributed PPO* (DPPO) [14]. Besides PPO, *Actor-Critic using Kronecker-factored Trust Region* (ACKTR) [59] also approaches TRPO’s shortcoming in sample complexity. ACKTR utilizes A3C’s advantage function and approximates the natural gradient with *Kronecker-factored Approximate Curvature* (K-FAC) [7, 25], which offers a comparable cost to SGD. By maintaining a running average of curvature information, K-FAC is able to reduce variance and achieves scalability, therefore ACKTR is more efficient in computing the inverse Fisher Information matrix. Further, ACKTR is not only able to increase the performance and sample efficiency compared to TRPO but also compared to the synchronous version of A3C - A2C [30].

## 4 Applications

One of the earliest success stories of deep reinforcement learning is TD-gammon [52] achieving master level performance in backgammon. TD-gammon was starting with zero prior knowledge and improved by solely playing against itself. However, consecutive experiments aiming to reproduce the success in backgammon for other games such as chess, Go and checkers failed. This was often attributed to the idea that state space exploration was helped by the stochasticity of the dice rolls [36]. Regardless of these failures, DQN was motivated by this success and showed that it was not only able to outperform existing methods on most of the Atari games, but even surpass human-level performance. RL algorithms following after DQN were able to improve the performance even further (e.g. A3C) or specifically improve on poorly performing games, such as h-DQN on Montezuma’s Revenge. Based on the idea of TD-gammon, AlphaGo [45] combines self-play with CNNs, supervised learning and *Monte Carlo Tree Search* (MCTS). In its core AlphaGo is selecting moves by a novel MCTS, which is guided by a learned value function and policy. However, instead of directly training from scratch, value function and policy are pretrained on human expert moves and are afterwards improved by self-play. In 2016 AlphaGo showed significantly better performance compared to other programs and was able to achieve the first victories over professional players. AlphaGo Zero [48] eliminates the supervised learning aspect from AlphaGo and uses no human data or guidance beyond the basic rules of the game. Additional improvements include an improved version of MCTS and the use of MCTS during training/self-play. AlphaGo Zero was able to defeat the strongest human players without a single loss and also beat AlphaGo considerably. AlphaZero [46] generalizes AlphaGo Zero to the chess and shogi domain. As a consequence, AlphaZero has to take different outcomes, e.g. draws, into account. Further, it is not able to exploit symmetries as in the game of Go. One major criticism for all three systems is the underlying computational power, e.g. training for AlphaZero was executed on 5,000 TPUs [18]. Therefore, it is questionable if the same algorithm performs equally well with less computational power.

Motivated by the idea of learning with zero human knowledge in AlphaZero, McAleer, et al. [26] apply this idea to Rubik’s cubes. DeepCube introduces *Auto-didactic Iteration* (ADI), a policy iteration motivated algorithm for joint training of value and policy network. The state space of the Rubik’s Cube was reduced

to avoid redundancies. Similar to AlphaZero they combine replay memory and MCTS, however they do not only search for the winning move but also the shortest one. For training they are working backwards and start scrambling a solved cube an increasing amount of time to create more complex samples after longer periods of training.

Besides the Atari games other video games have been explored in the context of reinforcement learning. This includes TStarBots [49] playing Starcraft II. One of the biggest challenges in Starcraft II is its large observation and action space. They evaluated DDDQN as well as PPO for this difficult task. The DDDQN model utilizes a Mixture of Monte-Carlo and bootstrapped Q-Learning returns as optimization target in order to approach the sparsity and long delay of rewards. Moreover, they apply multiple parallel environment instances to make training more efficient. When playing against the built in AI of Starcraft II, TStarBots performed well. In games against human players, TStarBots wins rarely. Similar to Starcraft II, Doom poses another high dimensional and complex task. A recent approach [43] combines DDQN with a recurrent neural network and PER. Moreover, they utilize snapshot ensembles in order to get multiple networks and more robust predictions. One limitation is their selected game mode, it does not require movement of the character. This avoids trading off between movement/exploration of the virtual space and defeating enemies. Consequently, the network only needs to learn spatial awareness to focus closer targets first. They showed improved results compared to previous methods, mainly based on the snapshot ensembling technique. The most recent success story is OpenAI Five and OpenAI 1v1 bot for Dota 2 [34]. They use a highly scaled version of PPO incorporating an LSTM module in order to approach the complex problem space. The training is done without prior human knowledge, but similar to AlphaZero the required computation makes it hard to reproduce the results reliably. OpenAI Five is able to defeat amateur human teams, whereas OpenAI 1v1 even defeats professional human players.

## 5 Conclusion and Discussion

Deep reinforcement learning has shown significant improvements and developments in the last years. This includes improving the sample efficiency and performance on a variety of different tasks. Challenging tasks such as the game of Go, Starcraft II or Dota 2 show (nearly) human level performance. In general, the literature indicates a trend towards off-policy learning methods. Replay memory allow to reuse samples and consequently make these algorithms more sample efficient. Furthermore, algorithms like PPO find popularity due to their performance and simple implementation.

Albeit these results look promising, deep reinforcement learning is currently not at the point to be universally applicable to all problems and domains. Especially neural networks can show large performance differences depending on hyper-parameter choices. Empirical results show converging evidence that neural networks perform well in practice but for now neural networks do not have any convergence guarantees. Based on this, algorithms like PPO often fail to present concrete mathematical explanations why they work. Another issue neural networks encounter, is the catastrophic forgetting. Once the task is learned, the network might forget entirely how solve the task after continuing training.



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