Notes on Reinforcement Learning and Deep Reinforcement Learning

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# Introductory Notes

What is Reinforcement Learning: branch of machine learning concerned with making decisions and taking sequences of actions based on some current state thereby maximizing some reward objective over time.

action

Environment

Agent

state, reward

Figure 1: Feedback loop between the Agent and the Environment in RL

The Agent and the Environment interact with each other on discrete timesteps creating a feedback loop depicted in Figure 1. The Agent has a goal of maximizing the cumulative reward while interacting with the Environment.

Observations in RL:

Robotics: camera images, joint angles

Actions in RL:

Robotics: joint torques

Rewards in RL:

Robotics: stay balanced, navigate to target locations

Approaches to RL

Dynamic Programming

Policy Optimization

Value Iteration

Policy Iteration

Policy Gradients

DFO / Evolution

Q Learning

Actor-Critic Methods

Two approaches to RL – the first approach is to optimize policy and the second one is dynamic programming.

Policy is the function which takes the observations with the state of the system and outputs actions. The Policy Optimization approach looks at the RL problem as an optimization problem trying to optimize the expected reward , there are parameters in the policy and we want find such set of parameters which maximizes the expectation of the stochastic reward. Posing the problem as an optimization problem ignores all of the structure of the problem conveyed through the Bellman’s equations.

# References

[1] [Deep Reinforcement Learning: Lecture 1: Intro, Episodic Reinforcement Learning and Markov Decision Processes, John Schulman, OpenAI, Berkeley (MLSS Cadiz, 2016)](https://youtu.be/aUrX-rP_ss4?si=cxFW4A2UwqBzVS_S)

[2] [Deep Reinforcement Learning: Lecture 2: More on Cross-Entropy Method and Value Functions, John Schulman, OpenAI, Berkeley (MLSS Cadiz, 2016)](https://youtu.be/oPGVsoBonLM?si=NMt3SSkhK1o22Uww)

[3] [Deep Reinforcement Learning: Lecture 3: More on Episodic Reinforcement Learning and Policy Gradients, John Schulman, OpenAI, Berkeley (MLSS Cadiz, 2016)](https://youtu.be/rO7Dx8pSJQw?si=h5v2bh-Se-CDV93I)

[4] [Deep Reinforcement Learning: Lecture 4: Performance of Policies, Policy Approximations, Parametrized Policies, Asynchronous Methods, John Schulman, OpenAI, Berkeley (MLSS Cadiz, 2016)](https://youtu.be/gb5Q2XL5c8A?si=6fYCJE75Kcs93Ldr)

[5] [Reinforcement Learning Course: Lecture 1: Intro to Reinforcement Learning, David Silver, DeepMind x UCL, 2015](https://youtu.be/2pWv7GOvuf0?si=4EW5Iv50whZLmrqE)

[6] [Reinforcement Learning Course: Lecture 2: Markov Decision Processes, David Silver, DeepMind x UCL, 2015](https://youtu.be/lfHX2hHRMVQ?si=wuSa7hl5sIcNBg7r)

[7] [Reinforcement Learning Course: Lecture 3: Planning by Dynamic Programming, David Silver, DeepMind x UCL, 2015](https://youtu.be/Nd1-UUMVfz4?si=8W0QmfwGtYJhSswb)

[8] [Reinforcement Learning Course: Lecture 4: Model-Free Prediction, David Silver, DeepMind x UCL, 2015](https://youtu.be/PnHCvfgC_ZA?si=pMy18AnRs8K0M6vX)

[9] [Reinforcement Learning Course: Lecture 5: Model-Free Control, David Silver, DeepMind x UCL, 2015](https://youtu.be/0g4j2k_Ggc4?si=wfbcjR3q_ui0exaU)

[10] [Reinforcement Learning Course: Lecture 6: Value-Function Approximation, David Silver, DeepMind x UCL, 2015](https://youtu.be/UoPei5o4fps?si=mhU3k64hfpL4r2kJ)

[11] [Reinforcement Learning Course: Lecture 7: Policy Gradient Methods, David Silver, DeepMind x UCL, 2015](https://youtu.be/KHZVXao4qXs?si=9YTXC1M--8bAdZpH)

[12] [Reinforcement Learning Course: Lecture 8: Integrating Learning and Planning, David Silver, DeepMind x UCL, 2015](https://youtu.be/ItMutbeOHtc?si=CiYa80AdWfH84TeT)

[13] [Reinforcement Learning Course: Lecture 9: Exploration and Exploitation, David Silver, DeepMind x UCL, 2015](https://youtu.be/sGuiWX07sKw?si=FMhQ1UKGpDOaTJLw)

[14] [Reinforcement Learning Course: Lecture 10: Classic Games, David Silver, DeepMind x UCL, 2015](https://youtu.be/kZ_AUmFcZtk?si=cVKj56KPGNrPabX6)

[15] [Learning Tetris Using the Noisy Cross-Entropy Method, Istvan Szita, Andras Loerincz, 2006](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/ReinforcementLearning/Learning_Tetris_Using_the_Noisy_Cross-Entropy_Method_Szita_2006.pdf)

[16] [Approximate Dynamic Programming Finally Performs Well In The Game of Tetris, Victor Gabillon et al, INRIA, 2013](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/ReinforcementLearning/NIPS-2013-approximate-dynamic-programming-finally-performs-well-in-the-game-of-tetris-Paper.pdf)

[17] [A Tutorial On The Cross-Entropy Method, Pieter-Tjerk de Boer et al, MIT, 2003](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/ReinforcementLearning/A_Tutorial_on_the_Cross-Entropy_Method_deBoer_2003.pdf)

[18] [The Cross-Entropy Method: A Unified Approach to Combinatorial Optimization, Monte-Carlo Simulation and Machine Learning, RY Rubinstein, DP Kroese, 2004](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/books/The_Cross_Entropy_Method_A_Unified_Approach_Rubinstein_Kroese_2004.pdf)

[19] [Application of the Cross-Entropy Method to the Buffer Allocation Problem in a Simulation-Based Environment, G. Allon et al, 2005](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/Application_of_the_Cross-Entropy_Method_to_the_Buffer_Allocation_Problem_in_a_Simulation-Based_Environment_Allon_2005.pdf)

[20] [Introduction to Rare Events Simulation, John F. Shortle, Pierre L'Eccuyer, Draft, 2011](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/Introduction_to_Rare-Event_Simulation.pdf)

[21] [The CMA Evolution Strategy : A Tutorial, Nikolaus Hansen, Inria, 2023](file:///The%20CMA%20Evolution%20Strategy%20/%20A%20Tutorial,%20Nikolaus%20Hansen,%20Inria,%202023)

[22] [Optimizing Walking Controllers for Uncertain Inputs and Environments, Jack M. Wang et al, 2010](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/Optimizing_Walking_Controllers_for_Uncertain_Inputs_and_Environments_Wang_2010.pdf)

[23] [Heavy Tails, Importance Sampling, and Cross-Entropy, Soren Asmussen, Dirk Kroese, Reuven Rubinstein, 2003](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/Heavy_Tails_Importance_Sampling_and_Cross_Entropy_Assmussen_2003.pdf)

[24] [Maximum Likelihood Theory for Incomplete Data from Exponential Family, Rolf Sundberg, U. of Stockholm, 1974](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/Maximum_Likelihood_Theory_for_Incomplete_Data_from_Exponential_Family_Sundberg_1974.pdf)

[25] [Maximum Likelihood from Incomplete Data via the EM Algorithm, A.P. Dempster, 1977](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/Maximum_Likelihood_from_Incomplete_Data_via_the_EM_Algorithm_Dempster_1977.pdf)

[26] [The EM Algorithm: An Old Folk Song Sung to Fast New Tune, XL Meng, 1997](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/The_EM_Algorithm_An_old_folk_song_sung_to_fast_new_tune_Meng_1997.pdf)

[27] [A Legacy of EM Algorithms, Kenneth Lange et al, 2023](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/A_Legacy_of_EM_Algorithms_Lange_2022.pdf)

[28] [The MM Alternative to EM, TT Wu, Kenneth Lange, 2011](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/The_MM_Alternative_to_EM_Wu_2011.pdf)

[29] [Nonconvex Optimization via MM Algorithms: Convergence Theory, Kenneth Lange, 2021](https://github.com/dimitarpg13/reinforcement_learning_and_game_theory/blob/main/articles/stochastic_optimization/Nonconvex_Optimization_via_MM_Algorithms-Convergence_Theory_Lange_2021.pdf)