# A Control Rearchers' Guide to the Reinforcement Learning Galaxy: A Survey

Zongqiang Pang,Liping Bai *Member, IEEE,*

***Abstract*—This paper is aimed at providing researchers in the field of control a bridge for incorporating deep reinforcement learning into their work. We are not talking about adding visual recognition capacity into end-to-end control loops, but technical details on how to take advantage of the progresses brought about by deep learning and its computational infrastructure. Off the shelf implementations of various reinforcement learning agents written in either PyTorch or Tensorflow can be easily found, yet, when control researchers venture into this subject, they would find out that there is still quite a lot caveats and pitfalls. They can't just formulate their control problem into reinforcement learning format and expect things to work. In this paper, we present the taxotamy of reinforcement learning from the perspective of optimization and we tease out the most important concepts while screening away ideas that is half-baked. We hope to provide control researchers ideas and clues as of how to further their research by riding the wave of reinforcement learning.**

***Index Terms*—Reinforcement Learning, Control Theory, Optimal Control, Optimization**

## I. Introduction

REINFORCEMENT learning is process of methotically extracting information from observations to gradually bound the policy distribution, either directly through policy gradient methods or via scaffolding measurements, such that the expected reward along a trajectory is maximized. This objective is similar to that of Trajectory Optimization which utilizes myriade of computational techniques to reveal the optimal trajectory embedded in the scripted dynamic equations. They are the "Black Box" approach and "White Box" approach perspectively, neither is perfect.

The "Black Box" approach requires copious amount of data. Efforts has been made to make it more broadly applicable and more efficient: Imitation learning and reverse reinforcemnt learning [1] aims at derive constraints from observed best solution; Sergey Levine utilizes unsupervised learning to build an agent with intuitions of the physical world [2]; Chelsea Finn introduced Meta-Learning [3] to extract overaching invariant structures from similar tasks with different setting. This line of research require firm grasp of statistical learning theory, information theory to design efficient schemes for exploration and minimize sampling collection. The "White Box" approach is based on classical control theories. It has a rich history and enjoyed broad success, yet despite effort from the best control theoriests, some complicated dynamics still elude mathematical scription.

Nanjing Unversity of Posts and Telecommunications, College of Automation & College of Artificial Intelligence, Nanjing, Jiangsu,210000 China email:zqpang@njupt.edu.cn

It is obvious that biological systems approaches control from both angles. Unfortunately, these two subjects are studied by two communities of researchers who use different notations to discribe the same processes and they publish their research only in journals of their own disciplines. In this paper, we hope to provide a bridge for researchers in the field of control theories who would like to incorporate reinforcement learning into their works. We are not the first ones to take up this challenge. Recently, there are interdiscipline conferences held specifially for the purpose of briding the gaps between these groups of people, for instance the L4DC (Learning for Dynamic Control) conference and Intersections between Control, Learning and Optimization Workshop.

In this paper, we build on the work of Benjamin Recht [4] to formulate reinforcelent learning in the language of optimization. The first barrier facing control researchers is consolidating the notation between control and reinforcement learning communities. Control communities use the notation system introduced by Lev Pontryagin. State is denoted $\mathcal{X}$, Action is denoted $\mathcal{U}$, which is the first letter of Russian for "Action", the dynamics and stocasticity is captured by physical model constraints $x_{t+1} = f(x_t, u_t, e_t)$ where e denote the noise of a system. The objective is usually to minimize the cost funtion $\mathcal{J}(.)$. Reinforcement Learning communities use the notation system introduced by Richard Bellman who studied dynamic programming. State is denoted $\mathcal{S}$, Action is denoted $\mathcal{A}$. The dynamics and stochaticity is captured via transition matrix $\mathcal{P}$ of a Markov Decision Process.The objective of RL is the maximize the reward function $\mathcal{R}(.)$. Yet, if we set the transition matrix to be identical to the noise, then it is clear that the underlying process behind these two notation system are exactly the same. The differences are nothing but style. Since the audience of our paper is the control community, we would cast reinforcement learning in the control notation system.

The second barrier facing the control researchings is the sense of standing on shifting sand instead of firm ground. For instance, while the convergence of dynamic programming method is proven, no guarantee can be found in the approximated version of the same algorithm; The asynchronous actor critic method obviously updates the parameters in a haphazard manner yet it works well empirically; the DQN method replace system function with the a specific form of Q function without theoretical proof, etc. For classically trained control researchers who is used to rigirous mathematical formalism, they may find the lack of theoretical support hard to palade. The idea of reinforcement learning is rather straight forward, what is hard is its implementation details.

This wave of innovation brought about by the reinforcement learning community is not just the implementation techniques, but also the computational infrastructure, notably the GPU emabled computing and the PyTorch, Tensorflow software packages. There are classical control algorithms that such as Differential Dynamic Programming can now be powered by those packages. We would also like to list the papers who adapt well known control algorithms for the newly available compuational platforms.

We first provide a taxotamy of reinforcement learning, then we elaborate on the enumerated path in section II and list all the important papers in this area of research. Finally, in section VII, we introduce how the compuational capacity unleashed for reinforcement learning algorithms can be better merged with well-known control algorithms.

## II. Where to Approximate

The constraints imposed in the Trajectory Optimization formulation manifest themselves directly in policy $\pi(x)$ and resulting in either a narrow band of trajectories or a single optimal solution. However, adjustments in the reinforecement learning formuation is not the policy per se but its distribution. Eventually, what we hope to acheive via learning is a policy distribution, either through policy gradient method or cost to go method, which would maximize the expected reward of a trajectory.

Reinforcement Learning is not a new subject, control researchers probably know it by the name Approximate Dynamic Programming. Yet the major progress in recent years is the enhanced compuation power which brought about the potential of neuronetworks as a universal approximator [5] to fruition. Most notably the series of wins reinforcement agents such as AlphaGo, AlphaStar forged against the best human players in the respective disciplines.

Broadly speaking, there are three revenues where neuronetwork based approximation can find its way into optimization as shown in 1. One is learning a dynamics model from samle; Second is policy gradient based learning; Third is approximation of cost to go functions such as value funtion and Q function. The details of the implementation would be specified in the subsequent sections.

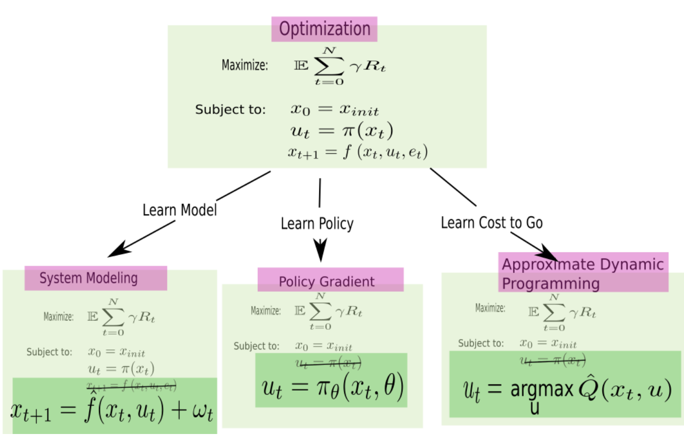



Fig. 1: From Optimization to Learning

Before we dive into the detailed researches in each category, we'd like to introduce additional mathematical tools and measurements that has been proven useful in merging reinforcement learning with optimization. One of the most important change of perspectives when control researchers ventures into the land of reinforcement learning is to formulate optimization as an inference problem [6]. Tranditional optimization would translate constraints imposed on the struture into definitive trajectories, subject to disturbance and correction. Yet inference view of optimization is an ever narrowing band od distribution as information trickles in via experiments.

There are two things control researchers should be aware of. One, if you simply apply reinforcement learning as it is written in Richard Sutton's book, it probably won't work for you. Additional statistical learning techniques are required. Two, Statistical learning is booming with ideas at this point. Every newly invented measurement and methods could be pretzeled into a self-sustainly structure if you know how to make such arguments, that does not mean it would be a useful tool for your research.

Here we point out two concepts: Mutual Information and Baysian NeuroNet, which have proven to be integral for converting optimization into an inference.

The go to text book for reinforcement learning community is that of Richard Sutton [7]. In the system contstructed by Richard, the objective of an agent is to maximize discounted reward. This formulation is proven a sound goal in the context of video games. However, for optimizations with a physics underpining, reward maximization is not adequate since noise and disturbances is common place in control.

Exploration and Exploitation trade off is something studied exhaustively in the reinforcement learning community. A common strategy is $\epsilon$ greedy policy where the value of epsilon decays as the learning progresses. Yet, the decaying rate is a hyperparater that need to be tuned. Is there are more sysmtmatical way to balance the exploration and exploitation trade-off? This is particularly important for control related training since this application has considerable amount of disturbance and noise. If the policy converges too soon, any subsequent disturce can deviate the trajectory to the extend that it is no longer controllable.

The intuition behind maximum entropy reinforcenement learning is the heuristic that when we don't know all the circumstance, we should prioritize options that could give us more choices regardless of how the system dynamics turns out to be. Statitically speaking, this means we should maximize the entropy of a distribution, which measures how uncertain or how broad the distributionb is.

The mathematical measurement used is mutual information [8]. It measures how much information regarding the random variable X is contained in the distribution of random variable Y. A reasonable question to ask is that out of all those measurements which captures "distance" in meansurement theory, why a divergence is chosen? Turns out, this choice is made because of its computational convenience, much like exponentials are chosen in integral transform because its nice features.

## III. System Modelling

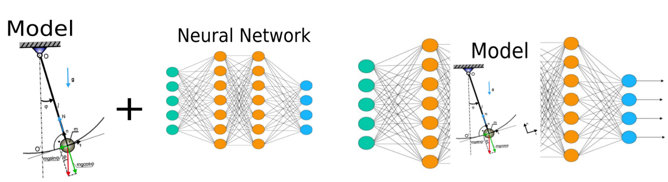
There are two ways for collecting data of the system. One is offline. Just collecting as much trajectories as possible about this system and then build the model later. Second is online data collection where a sample is collected and then incorporated into the model building process right away.

Strictly speaking, offline data collection based model building belongs to the domain of System Identification rather than reinforcement learning. But since it is tangentially related to our paper, we still list it here. After the data is collected and a system model is trained from offline data, an appropriate controllers can be computed based on that model. There are numerous applications in this line of research, supposedly the first successfully implemented non-linear controller based on this method is that of Caltech's Neural Lander. [9]

Model building in the reinforcement context really refers to the only data collection and model refinement process. This model training process doesn't have to start from scratch, althought that is certainly an option. Most likely there already exist a model that partially describes the system. It would be more efficient if we can somehow combine that partial model with a neural network, which would capture the unmodelled dynamics via online training.

ONLINE MIRROR DESCENT. BRYAN BOON'S WORK ON PATH PLANNING AND REINFORCEMENT LERANING

A existing model can be additively combined [10] with a neural network, or it can be embedded into a neural network [11] as shown by Fig. 2. Optimization solver can also be embedded in the neural network as a laywer to encourage faster convergence. [12] [13] [14].




(a) Additive (b) Embedding

Fig. 2: Combine Model and Neural Net

While in theory the aforementioned modelling method should work, in practice it is proven to be far from optimal. [15]. One possible explanation is that any overfitting of the model along the way would be difficult to overcome by subsequent training, resulting in suboptimal performance. One solution is to measure uncertainly of the model with Bayesian Neural Network.

The venena formulation of neuronetwork is one where the weight of each neuron $w_i$ is a single number, which is adjusted based on the backward propogation process. Baysian Neural Network(BNN) is a network where the weigh is subject to a parameterized distribution as shown in Fig. 3

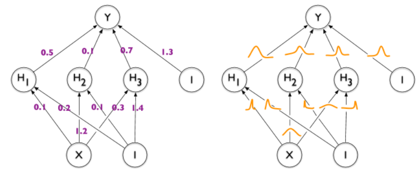


Fig. 3: Neural Network and BNN

BNN is used to measure the uncertainly of the model and better choices can be made when uncertainly of the model is part of the decision making process. [16]

THIS IS THE PART ABOUT BAYSIAN REINFORCEMENT LEARNING

The collected data can be used to train a model which informs which actions should be chosen. It can also be used to train the policy distribution either directly or through policy gradient. The direct policy training method is a theoretical possibility, but due since the number of actions along a trajectory is usually rather large, the valishing gradient problem facing this methods makes it had to implement. In this paper,we focus our discussion on the Policy Gradient Method.

When control researchers are first exposed to the proof of policy gradient method provided in Richard Sutton's book, they would find it difficult to swallow. The notations are tidious and the logic non-rigirous. A better proof was only recently presented. Please refer to this paper for policy gradient derivation. [17]

## IV. Policy Gradient

## V. Approximate Dynamic Programming

1. MAX entropy 2. the formulation of cost to go without a system model

## VI. Other Ways to Utilize Increased Computational Power

### A. Multiagent Formulation

### B. Monte Carlo Tree Search

### C. Random Shoot

One of the corrilary of the development of reinforcement leraning is improvement in computational infrastructure, which is something the control community can take advantage of. Before this wave of hype in machine learning, GPU enabled computation was a specialty knowledge that is only accessable to large corporations. But now, with CUDA and related software, such compuational power is as easy

Random shoot is the idea if rolling out trajectory at random and wht the fuck is random shoot?

## References


[1] J. Ho and S. Ermon, "Generative adversarial imitation learning," in *NIPS*, 2016.

[2] C. Finn, I. J. Goodfellow, and S. Levine, "Unsupervised learning for physical interaction through video prediction," *ArXiv*, vol. abs/1605.07157, 2016.

[3] C. Finn, P. Abbeel, and S. Levine, "Model-agnostic meta-learning for fast adaptation of deep networks," *ArXiv*, vol. abs/1703.03400, 2017.

[4] B. Recht, "A tour of reinforcement learning: The view from continuous control," *ArXiv*, vol. abs/1806.09460, 2018.

[5] K. Hornik, “Approximation capabilities of multilayer feedforward networks,” *Neural Networks*, vol. 4, pp. 251–257, 1991.
[6] S. Levine, “Reinforcement learning and control as probabilistic inference: Tutorial and review,” *ArXiv*, vol. abs/1805.00909, 2018.
[7] R. Sutton and A. Barto, “Introduction to reinforcement learning,” 1998.
[8] S. Kullback and R. A. Leibler, “On information and sufficiency,” *Annals of Mathematical Statistics*, vol. 22, pp. 79–86, 1951.
[9] G. Shi, X. Shi, M. O’Connell, R. Yu, K. Azizzadenesheli, A. Anandkumar, Y. Yue, and S.-J. Chung, “Neural lander: Stable drone landing control using learned dynamics,” *2019 International Conference on Robotics and Automation (ICRA)*, pp. 9784–9790, 2019.
[10] L. Hewing, K. P. Wabersich, M. Menner, and M. N. Zeilinger, “Learning-based model predictive control: Toward safe learning in control,” 2020.
[11] A. Mohan, N. Lubbers, D. Livescu, and M. Chertkov, “Embedding hard physical constraints in neural network coarse-graining of 3d turbulence.” *arXiv: Computational Physics*, 2020.
[12] F. de Avila Belbute-Peres, K. Smith, K. R. Allen, J. Tenenbaum, and J. Z. Kolter, “End-to-end differentiable physics for learning and control,” in *NeurIPS*, 2018.
[13] F. de Avila Belbute-Peres, T. D. Economon, and J. Z. Kolter, “Combining differentiable pde solvers and graph neural networks for fluid flow prediction,” *ArXiv*, vol. abs/2007.04439, 2020.
[14] A. Agrawal, B. Amos, S. Barratt, S. P. Boyd, S. Diamond, and J. Z. Kolter, “Differentiable convex optimization layers,” *ArXiv*, vol. abs/1910.12430, 2019.
[15] A. Nagabandi, G. Kahn, R. S. Fearing, and S. Levine, “Neural network dynamics for model-based deep reinforcement learning with model-free fine-tuning,” in *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 2018, pp. 7559–7566.
[16] C. Blundell, J. Cornebise, K. Kavukcuoglu, and D. Wierstra, “Weight uncertainty in neural networks,” *ArXiv*, vol. abs/1505.05424, 2015.
[17] J. Schulman, S. Levine, P. Abbeel, M. I. Jordan, and P. Moritz, “Trust region policy optimization,” in *ICML*, 2015.