Benchmarking Real-Time Reinforcement Learning

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Abstract

Decision-making algorithms can require fast response time in applications as diverse as self-driving cars and minimizing load times of webpages. Yet, modern algorithms (deep reinforcement learning) are usually developed in scenarios where inference and training computational costs are ignored. This proposal aims to study reinforcement learning and control algorithms for real-time continuous control. In this scenario, the environment continuously evolves while actions are being computed by the agent (either in training or inference). The first goal is to provide a clear picture of the performance of modern algorithms modulated by their computational costs. The second goal is to identify the major challenges that arise when considering real-time environments to guide further research.

1 Introduction

Recent advances in machine learning (deep learning) have been driven by models with significant computational costs [Goodfellow et al., 2016; Brown et al., 2020]. Furthermore, the majority of the research community is focusing on maximizing accuracy, as reflected by the benchmarks [Deng et al., 2009; Mnih et al., 2013] which ignore computational costs. This trend leads to research improvements that are driven by increasing training data[1].

However, in the real world, slow computations can lead to negative outcomes. For a self-driving car, the computation time of deciding when to brake can have a life-changing impact. In a real-time setting, the environment will keep evolving while the next action is being selected. This can create many complications such as: 1) the action selected might not be relevant anymore, 2) the agent might enter an irreversible part of the environment (a car crash for example).

Starting in the 1960s, the control theory community considered mathematical frameworks to satisfy real-time constraints [Nelson, 1965; Rabin, 1963] that arise when doing control in a time-sensitive environment. The theory was considered for controllers in embedded devices with safety-critical applications such as space navigation [Hamlin, 1964]. Formally, real-time control focuses on finding a controller guaranteeing the stability of the policy if inference is performed under a time threshold T. The need for real-time machine learning has also been identified in different areas of the field such as computer vision [Galoogahi et al.; Li et al., 2020] or speech translation [Bangalore et al., 2012].

[1]It has been suggested that the majority of the improvements of machine learning come from increased computational power and not algorithms [Sutton, 2019; Radford et al., 2018]. This supports the need to consider the performance of an algorithm modulated by its energy use as suggested by [Welling, 2018].

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In recent years, reinforcement learning algorithms combined with flexible non-linear models (e.g. deep neural networks) have demonstrated a remarkable ability to solve complex environments [Mnih et al., 2013; Schulman et al., 2017] at the costs of high sample and computational complexity. Deep reinforcement learning algorithms usually interact with a simulator without time constraints on inference or training. This creates a gap between these solutions and many real-world applications where action selection can be temporally and computationally constrained. The majority of existing benchmarks ignore this discrepancy. The motivation of this work is to analyze the performance of modern algorithms in the context of real-time control.

The aim is to address the following two goals:

Goal 1: Analyze the performance trade-off between computationally complex and simple algorithms in the context of real-time decision-making. This analysis can be used to define which algorithm to use depending on the time requirements as well as the complexity of the environment.

Goal 2: Exploratory analyses of the algorithmic issues arising when working in real-time. This can help guide the research community in the future on the most pressing issues to be addressed before modern algorithms can be deployed in time-sensitive applications.

We consider a continuous control benchmark to compare the performance of control and RL algorithms on robotic environments with varying difficulty. The real-time aspect is emulated by running the agent's algorithm and the environment together in parallel (illustrated in Figure 1). The difficulty of the tasks can be scaled by increasing or slowing down the speed of time in the environment's simulation. We consider several tracks with varying amount of computational power available to underline the sensitivity of RL algorithm to computational considerations. The goal is to compare a wide array of methods from control and reinforcement learning using simple (linear) and flexible models (non-linear). This real-time benchmark enables a new way to compare algorithmic decisions such as model-free versus model-based RL which have different computational profiles for training and inference.

2 Related work

The two leading frameworks for sequential decision-making environment are control theory [Lee and Markus, 1967] and reinforcement learning [Sutton and Barto, 2018]. Both attempt to model sequential decision-making, however, control theory has a strong emphasis on models, sample efficiency, and theoretical guarantees. In contrast, reinforcement learning is more focused on learning from experience and data.

Real-time control considers the problem of creating a policy with guaranteed performance if the output is produced within a given fixed time window T [Kwon and Pearson, 1980]. Several works have expanded the scope of those algorithms to accommodate for uncertainty over the time horizon T and the dynamics [Cucu-Grosjean, 2013; Santinelli and Cucu-Grosjean, 2015]. Theoretically, the performance is guaranteed by modelling the control problem as applying the action with a deterministic delay. Mathematically, this is often done using functional ordinary differential equations [Hale, 1971], which are a generalization of ODE where the inputs can be several timesteps before. A similar strategy was developed in Reinforcement learning to model for the delay of applying an action [Chen et al., 2021; Bouteiller et al.; Derman et al., 2021; Ramstedt and Pal, 2019].

Practically, the delay in all the works mentioned above is implicitly modelled by looking for a policy that will perform well even if the action is applied with a specific delay. For example, this can be done using policy gradient where the rewards correspond to the evaluation of the delayed policy. This in contrast to explicit modelling of the delay that could predict the state in the future using a dynamical model and optimize with respect to this prediction.

The key aspect in the RL works mentioned above is that the delay applied is independent of the computation performed. It is usually a fixed quantity used to demonstrate the property of the algorithms. The proposed research pushes this one step further by experimentally making the delay proportional to the computational costs of the algorithm used. Practically, this means that any computation spent by an algorithm will result in a delay for the action to be taken. This enables a new way of comparing algorithms where performance is modulated by computation costs.

3 Methodology

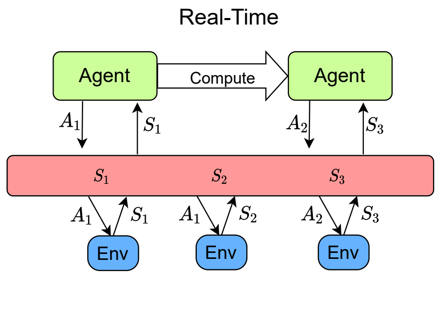

Figure 1: Diagram of the interactions between the environment and the agent. S represent the state and A the action. The left diagram represent the real-time interaction with an environment. As you can see the action A_1 is being repeatedly applied until the new action A_2 is computed. The right diagram represents how RL algorithms are trained when the state is frozen during action selection.

We consider a Markov Decision Process defined as a tuple $\{S, A, T, R\}$ where S represent the set of states, A the set of actions, $T(s'|s,a) : S \times A \to S$ the transition function and $R(s,a) : S \times A \to \mathbb{R}$ the reward function.

In continuous control, both the state ($s \in S$) and action ($a \in A$) are usually continuous and belongs to $\mathbb{R}^N$. The goal is to accumulate rewards over N time steps and maximize the following quantity:

$$\mathbb{E}_a[\sum_{i=0}^{i=N} \gamma^t R(s,a)|s_0] \quad a \in A, s \in S. \tag{1}$$

where s_0 is the starting state. Theoretically, the appropriate definition of this process should consider continuous time due to the desire to benchmark algorithms in *real-time*. We present the discrete version due to the fact that almost all control algorithm are concretely solving discrete version of the process and the mathematical complexity introduced by the continuous time version is not necessary for this paper. Experimentally, by taking a time discretization steps small enough, it is possible to emulate continuous time. Theoretically, an equivalence between discrete and continuous time MPD can developed [Serfozo, 1979].The real-time aspect of the environment is emulated using sticky actions. This means that until the agent decides on a new action, the previous one will be applied, a natural concept in continuous control (illustrated in Fig 1).

3.1 Control models

From a reinforcement learning and control perspective, the challenge is to accumulate as many rewards as possible with the caveat that any computation performed by the algorithm will translate into time lost in the execution of this action. We consider several axes of comparison between decision-making algorithms. The methods considered and their characteristics are detailed in Table 1.

Table 1: Table describing the characteristics of the methods considered. MF model-free, MB model-based, H hybrid model-based and policy, LM linear model, NLM non-linear model, RR real-time robustness.

	MF	MB	H	LM	NLM	RR
Random policy [Mania et al., 2018]	x			x		
SAC [Haarnoja et al., 2018]	x				x	
Real-time RL [Ramstedt and Pal, 2019]	x				x	x
MPC linear dynamics		x		x		
Muzero [Schrittwieser et al., 2020]			x		x	

The first axis considers the computational costs of running the decision-making algorithm. There exists a long-standing debate between methods that include an explicit model of the dynamics of the environment (model-based RL, control algorithm) and those that don't (model-free). While it is easy to argue that a model of the environment should improve generalization and performance, it often comes at higher computational costs. As an extreme, performing Monte-Carlo roll-out in chess may lead to an optimal answer, however, computing the full tree is intractable. In those cases, algorithms often cut the tree by using a policy (model-free algorithm). In this paper, we call those methods hybrid. Practically, model-based methods display fast training time but slow inference time due to the necessary roll-out. Lower policy training time can lead to more frequent policy updates and better data collections. In contrast, model-free methods will display quick inference time which can lead to more timely response and improved stability.

The second axis concerns the computational costs of the learning algorithm involved. While training a deep neural network could enable higher performance on complex locomotion tasks, it incurs significant computational costs (inference and training) potentially hindering performance. It will be interesting to compare its performance to simpler models (linear regression) that are computationally efficient but have less flexibility.

Finally, we also include two methods developed to adapt to the real-time setting, one from RL [Ramstedt and Pal, 2019] and one from control [Zeilinger et al., 2014].

3.2 Software considerations

While the algorithmic side of things is essential, as illustrated earlier in this proposal, computation and algorithm are intricately connected. It is essential to study the software specifications of the problem.

The first one concerns the simulation of the real-time environment. One option is to run an environment in a separate thread(CPU) which will result in a simple interface, however, the step frequency will be varying based on the computational speed of the machine considered (this may be controllable). This could render benchmark between different research groups complicated. The second option would be to use internal clocks to measure the time spend on computations and pass this information onto the environment. The issue with this approach is that it creates a synchronous paradigm where state and actions can not be easily shared asynchronously. The decision on how to implement the environment is not fixed yet, but the second option seems easier for reproducibility purposes.

4 Experimental protocol

This proposal focuses on continuous control environments due to their direct applicability for real-world problems. Furthermore, continuous control is strictly a more general problem than turn-based environments [Mnih et al., 2013] with a time limit because the environment keeps evolving while one runs the computations.

The first step is to benchmark 4 popular control environments based on the Mujoco simulator [Todorov et al., 2012]: inverted pendulum, half-cheetah, hopper, and humanoid [Ellenberger, 2018–2019]. The environments considered range in difficulty from the inverted pendulum (1 degree of freedom) to the humanoid (24 degrees of freedom). The range of difficulty considered should be wide enough to allow deep reinforcement learning algorithms to outperform simpler models at the expense of higher computational costs.

The second set of environments attempts to solve manipulation tasks such as fetchpickandplace and handmanipulategg. Finally, we also consider a vision-based environments with high-dimensional input, where the goal is to drive a car on a track [Ramstedt and Pal, 2019]. This will enable to get a better sense of when deep learning architecture are superior to linear approximators even though the computational costs is greater.

4.1 Metrics

The main metric of interest is the cumulative reward described in Equation 1. However, as illustrated in [Henderson et al., 2018], the variance of the return can vary greatly depending on the seed used. This underlines the brittleness of deep RL methods and the need for a thorough evaluation of the variance profile of the reward before drawing any conclusion. The main strategy is to run the algorithm on multiple seeds (10+) and analyze the performance profile of the return [Henderson et al., 2017; Jordan et al., 2020]. Hypothesis testing can be used to compare the relative performance of different algorithms. Based on each environment, it can be interesting to display a 2 dimensional scatter graph displaying the performance of each algorithm based on its computational cost. This could be used to guide a decision on which algorithm to use in which context.

4.2 Discretization factor

There exists two ways to simulate real-time interaction in a discrete system. The first one consists of using dynamic time steps in the physics simulator. Most simulators use sampling-based solutions to solve the complex ODE underlying the environment considered and varying time steps could be passed. The issue with this method is that it involves re-compiling the environment every time the time step is changed. The other method is to set the timestep in the environment to be small and run the environment quickly. We will implement the latter one due to its simplicity.

The difficulty of the environment can be scaled by increasing or slowing down the environment's loop. Practically, 1 second of compute can be equal to 0.1 or 0.01 seconds spent in the environment.

4.3 Compute resources available

Practical applications of decision-making algorithms can be resource-constrained. For example, in embedded devices, the decision algorithm may only have access to one CPU. We assume one thread(CPU) is reserved for simulating the environment. Based on the amount of processing power available, we consider three experimental tracks:

Track 1: We first train a policy in a simulator without time constraints and then evaluate its performance in real-time. This track focuses on the delay induced by the computational costs of inference. There is not computational constraints on the inference mechanism, any number of GPU's or CPU's can be used in this track. This represents an important benchmark for deploying controllers in the real-world.

Track 2: The setup is similar to track 1, except that the controller is restricted to 1 CPU for inference. This is meant to represent the challenge of restricted available compute in embedded device. In this scenario, it will be interesting to study the performance of deep learning architectures due to the potentially slow inference on CPUs.

Track 3: The agent has access to CPUs and GPUs but both training and inference result in delay for action selection. The challenging aspect of this track is that most algorithms are not tuned nor developed for this setting. For most deep reinforcement learning algorithms, how often to alternate between training and inference is not clear. Furthermore, in DRL, the training time is so large that it will fail many episodes before ending training. However, this is the expected behaviour. The goal is to display how some of those algorithms fail in this regime and how some may succeed (real-time MPC). The goal is to analyze performance as the algorithm are currently being used. While further tuning of each algorithm could improve the performance it is not the focus of this benchmark.

4.4 Reproducibility

One of the challenging aspects of this benchmark is that reproducibility may be difficult to achieve. We discuss below some of the issues that will be encountered and the steps towards mitigating reproducibility concerns.

- Different hardware (CPU, GPU) will lead to different inference times and performance. The results reported will only be valid for a specific compute engine and experiments will need to be re-run in a different environment. Docker will be used to make sure the software environment remains the same and improve cross-platform portability.
- Due to the priority process of commonly used OS (Linux), background processes can interrupt and delay computations of our scripts. We take a statistical approach where the interruptions should be averaged out over multiple runs. We will also perform an analysis of the variance of the computation time of each step to confirm that the results are coherent.

Finally, we will attempt to minimize any other CPU work happening on the machine to minimize preemption. This can also be done by increasing the priority of the python script.

- We will record the computation time of the various steps and report all the relevant metrics in a publicly accessible wandb dashboard.

5 Discussion and Conclusion

To summarize, the goal of this work is to give an objective assessment of the performance of real-time decision-making algorithms in continuous control. The second motivation is to analyze the challenging aspect of real-time decisions such as to underline interesting research questions for the community. One interesting aspect of this benchmark is that it raises other research questions such as:

- When computing the next action, how does an agent process a new incoming state or reward? Should the agent be able to interrupt the currently running computation and implement a priority system?
- How much time should an agent spend on inference (state and environment-dependent)?
- How to allocate time between training and inference?

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