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Chapter 1

Preliminaries

In this chapter we provide an introduction to the Multi-Armed Bandit framework and the Reinforcement Learning framework, which are the two frameworks of reference of this thesis project. The Reinforcement Learning section is opportunely preceded by an overview of Markov Decision Processes, which are the building blocks of Reinforcement Learning. Then, we present a particular class of strategies to solve the Reinforcement Learning problem: Policy Search methods. The aim is to introduce concepts that will be used extensively in the following chapters.

1.1 Multi Armed Bandits

Consider a situation in which a gambler (the *agent*) is sitting in a casino, staring at a number of slot machines from which he wants to pick the most profitable one and play with it all night long. Each slot machine is characterized by a certain *mean reward*. The objective of the gambler is to maximize the gains that he will have won by the end of the night, but, unfortunately, he can not know *a priori* the mean reward associated to each slot machine. Hence, the gambler must find a suitable strategy in order to effectively *explore* his possibilities, by testing the different slot machines, and, then, *exploit* the ones that prove to be more profitable. In fact, the gambler would face an equivalent problem if he was to play a single machine with as many *arms* (levers) as the number of slot machines present in the casino, each with its own specific mean reward. Hence the name **Multi Armed Bandit (MAB)** [68] given to this problem, in homage to the one-armed bandit, an old-fashioned name for a lever operated slot machine ("bandit" because it steals your money). In the artificial intelligence literature,

MAB refers to a broad class of problems that can be formulated as this gambling learning problem. Of course, **MABs** have other, more valuable, applications other than gambling. Current applications span from web interfaces configuration, news recommendation, dynamic pricing, ad placement, networking routing and game design.

Definition 1.1.1. (Multi Armed Bandit) A **MAB** is a tuple $\langle \mathcal{X}, \mathcal{R} \rangle$, where:

- (i) \mathcal{X} is the $d_{\mathcal{X}}$ -dimensional set of possible arms, or actions, that the agent can pick; \mathcal{X} can be discrete or continuous, one dimensional or multi-dimensional, finite or infinite.
- (ii) $\mathcal{R} : \mathcal{X} \rightarrow \Delta(\mathbb{R})$ is an unknown function of rewards such that for every $x \in \mathcal{X}$ it assigns a probability measure $\mathcal{R}(\cdot|x)$ over \mathbb{R} .

One can think to the set of possible arms and reward functions associated to them as the *environment* the learner interacts with. According to the specific characteristics of the environment, there exist a broad taxonomy of **MABs**. For our reader, it is sufficient to know that in this work we deal with *stochastic stationary bandits*. In this case, the environment is restricted to generate the reward in response to each action from a *probability distribution* $\mathcal{R}(\cdot|x)$ that is specific to that action, stationary along time and independent of the previous action choices and rewards. For example, the reward distribution could be Gaussian or Bernoulli. The expected reward of the stationary distribution associated to arm x is noted $\mu(x) = \mathbb{E}_{r \sim \mathcal{R}(\cdot|x)}[r]$.

The **MAB** game is played sequentially by a *learner* over multiple rounds $t = 1, 2, \dots, T$, up to the *horizon* $T \in \mathbb{N}$, which depends on the problem at hand. Evidently, the agent can have memory but can not foresee the future. Thus, the current action x_t should only depend upon the sequence of previous actions and rewards, the *history* $\mathcal{I} = \{x_0, r_0, x_1, r_1, \dots, x_{t-1}, r_{t-1}\}$. A *policy* is a mapping from histories to actions which represents the behaviour of the agent, its strategy. the first question which springs to mind is then: how can we evaluate the quality of a policy? To this aim, the literature extensively adopts a performance measure called the *regret*;

Definition 1.1.2. (Immediate Regret) The *immediate regret* suffered by a learner at round t is:

$$\Delta_t = \mu(x^*) - \mu(x_t) \quad (1.1)$$

where $x^* \in \arg \max_{x \in \mathcal{X}} \mu(x)$ is an arm with the highest expected reward i.e., an *optimal arm*.

Definition 1.1.3. (Regret) *The regret of a learner is the cumulated sum of the instantaneous regrets:*

$$\text{Regret}(T) = \sum_{t=0}^T \Delta_t \quad (1.2)$$

The quality of a certain policy is then given by the rate of growth of the regret as the horizon T grows. A good learner achieves sub-linear regret, which means that $\text{Regret}(T) = o(T)$ or, equivalently, that $\lim_{T \rightarrow \infty} \text{Regret}(T)/T = 0$. For example, some state of the art policies for different bandit settings have regrets close to $O(\sqrt{T})$ or $O(\log(n))$ [72]. The regret has two characteristics that make it a good performance metric. First, it supplies a degree of normalization because it is invariant under translation of rewards. Second, it represents the price paid by the learner for not knowing the true environment. Anyway, a crucial aspect for designing a sub-linear regret policy is to carefully balance the trade-off between exploration and exploitation that characterizes all bandits.

1.1.1 Exploration and exploitation

In order to maximize its cumulative reward, a bandit agent must prefer high-reward arms discovered in past rounds. But to discover such arms, it has to spend a certain amount of rounds trying arms that it has not selected before. In other words, the agent has to *exploit* the most profitable actions revealed in the past, but it also has to *explore* in order to make better action selections in the future. If the reward function is stochastic as in stationary stochastic bandits, even more resources should be dedicated to exploration, because one trial is not enough to have a good estimate of the expected reward of one arm. In fact, the exploration-exploitation trade-off is a well known mechanism that goes back to psychology and it affects us all in our daily lives. Take, for example, a typical lunch break on a working day. Say that your favourite restaurant is right around the corner. If you go there every day (*exploitation*), you will be confident of what you will get, but miss the chances of discovering an even better option. On the contrary, if you try new places all the time (*exploration*), you are very likely going to eat unpleasant food from time to time. The sweet spot is usually in between these two extreme options and a crucial challenge for any bandit algorithm is to properly balance between exploration and exploitation. As we will see, this dilemma arises in *reinforcement learning* too and will be at the very core of our discussion.

Now, we proceed by briefly sketching out two bandit settings that are of central

interest to this work.

1.1.2 Stochastic Bandits With Finitely Many Arms

An important declination of the bandit problem, much studied in the literature [72], is the stationary stochastic bandit problem with *finitely many arms*, i.e., stationary stochastic bandits whose action space consists of a discrete arm set $|\mathcal{X}| = K \in \mathbb{N}_+$. This setting is particularly important because of its simplicity, which makes it a perfect starting point for understanding the exploration-exploitation trade-off and for designing algorithms that can be extended to more complex settings afterwards. Also, many real world applications can be modeled as finitely-armed stationary stochastic bandits.

In order to deepen our understanding of this setting, and of the bandit problem in general, let's discuss the most simple policy that one can imagine: the *explore-then-commit* algorithm. Basically, this policy consists in choosing each arm a certain number of times m and subsequently exploit by playing the arm that appeared to be the best after exploration. Because there are K actions, the algorithm will explore for mK rounds before choosing a single action for the remaining rounds. The choice of the agent goes to the arm i with the highest average pay-off received up to round t :

$$\hat{\mu}_i(t) = \frac{1}{T_i(t)} \sum_{s=1}^t \mathbb{1}_{\{x_s=i\}} r_s \quad (1.3)$$

where $T_i(t) = \sum_{s=1}^t \mathbb{1}_{\{x_s=i\}}$ is the number of times up to round t the agent picks action i . Algorithm 1.1 shows the pseudo-code of the explore-then-commit policy. Recall $\forall a, b \in \mathbb{N}^+, a \bmod b = a - b\lfloor a/b \rfloor$.

It suffices a quick glance to the algorithm to have a tangible demonstration of the importance of the trade-off between exploration and exploitation. This is confirmed by the analysis of the regret.

Theorem 1.1.1. [72] *The expected regret of the explore-then-commit policy is bounded by:*

$$\text{Regret}(T) \leq \min\left(m, \left\lceil \frac{T}{K} \right\rceil\right) \sum_{i=1}^K \Delta_i + \max(T - mK, 0) \sum_{i=1}^K \Delta_i \exp\left(-\frac{m\Delta_i^2}{4}\right) \quad (1.4)$$

where Δ_i is the immediate regret of arm i as defined in 1.1.2.

Algorithm 1.1 Explore-then-commit

- 1: **Input:** $m \in \mathbb{N}$
- 2: **for** $t = 1, \dots, T$ **do**
- 3: Choose arm

$$x_t = \begin{cases} i, & \text{if } (t \bmod K) + 1 = i \text{ and } t \leq mK \\ \arg \max \hat{\mu}_i(mK), & \text{if } t > mK \end{cases}$$

- 4: **end for**
-

Evidently, if m is large the policy explores for too long and the first term will be eventually too large. On the other hand, if m is too small, then the probability that the algorithm exploits the wrong arm will grow and the second term will become too large. Explore-then-commit is an evident case of undirected exploration: during the exploration phase, all the arms are pulled uniformly without leveraging any information that the agent collect in the process. In the next chapter, we will present various techniques that tackle the exploration problem in a more directed way.

1.1.3 \mathcal{X} -armed bandits

Another stationary stochastic bandit setting interesting to our scope is the *continuum-armed bandit* setting [2]. Here, the arms are chosen from a subset of the real numbers $\mathcal{X} \in \mathbb{R}^{d_{\mathcal{X}}}$, hence, the action space is infinite. Moreover, the mean rewards are assumed to be a continuous function of the arms. An example of such bandits are continuous *Lipschitz bandits* [74], where the expected reward is a Lipschitz function of the arm. This assumption is extremely useful because it implies that the information obtained by selecting one arm can be shared to its neighbouring arms. Thus, exploration can be made more efficient, and possibly directed, by exploiting the correlation between arms. Indeed, when the set of arms is infinite it is necessary to make some assumption on the correlation between arms. If arms can not share any information, learning become unfeasible. \mathcal{X} -armed bandits [27] are a further generalization of this setting where the set of arms, \mathcal{X} , is allowed to be a generic measurable space and the mean-payoff function is *weak Lipschitz* with respect to a dissimilarity function that is known to the decision maker.

By now, the reader should have noticed that a distinguishing feature of bandit

problems is that the learner never needs to plan for the future. More precisely, in bandits we invariably make the assumption that the learner's choices and rewards tomorrow are not affected by its decision today. In the next chapter, we discuss a more general framework that includes this kind of long-term planning.

1.2 Markov Decision Processes

A **Markov Decision Process (MDP)** is a more powerful way to model the interaction between an agent, which is the learner and the decision maker, and an environment. When the agent performs an action a , the environment responds presenting a new state s to the agent and rewarding the agent with a certain scalar signal called *immediate reward*. Importantly, the environment dynamics of a **MDP** are *stationary*, i.e., they do not depend upon time. Moreover, the state s_{h+1} at time step $h + 1$ must depend only on the previous state s_h and action a_h . This property, called *Markovian Property*, entails that the agent can forget the states and actions of the past. Still, differently from what happened in bandits, the current state and set of possible actions and subsequent rewards the agent faces, are determined by his previous choice. This is a strong mechanism that encourages the agent to take into account the consequences of its choices over time. On top of this, there is another mechanism that makes the agent even more concerned by long term consequences. In fact, the objective of the agent is to maximize over time the *cumulative reward* or *return*, which is the cumulated sum of the immediate rewards obtained after each action undertaken by the agent. Evidently, sometimes it is more profitable to sacrifice immediate reward in order to reach a higher cumulative reward in the long term. This mechanism pushes the agent to take into account the future in its current decisions.

Hence, **MDPs** are a powerful tool capable of modelling many challenges that we encounter in life, science and engineering. Take, for example, a hungry newborn infant in his mother's arms. Through various attempts, the infant moves around his arms, head and mouth looking for food. In this way, he changes its state until the moment he eventually receives a positive reward, the mother's milk. Little by little, the baby will learn the precise sequence of actions and states that rewards him with milk. Having understood the general principles underlying **MDPs**, we can now move to a formal definition.

Definition 1.2.1. (Markov Decision Process) *A continuous **MDP** [100, 119] is a tuple $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma, \mu \rangle$, where:*

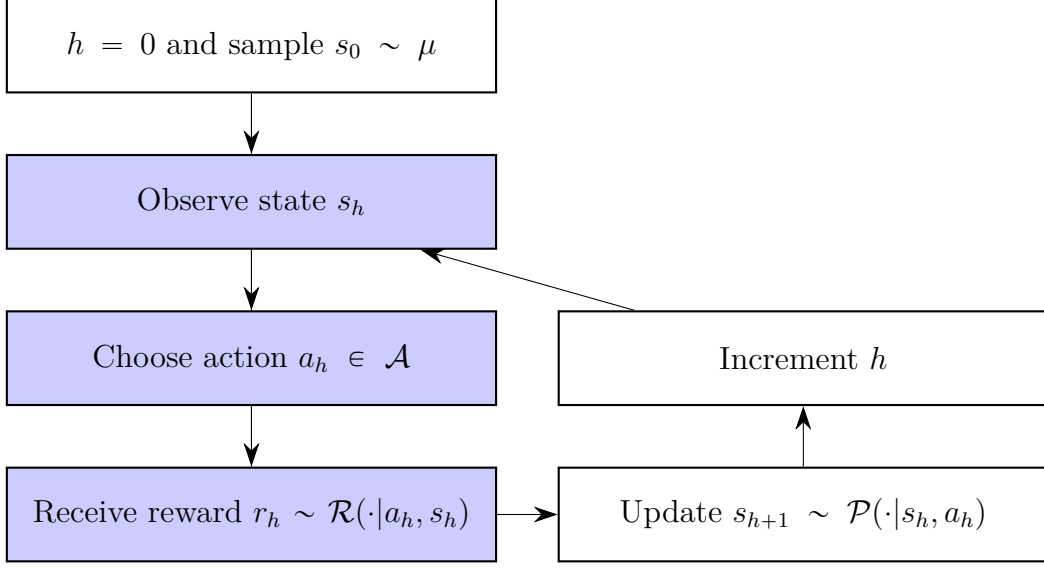


Figure 1.1: Interaction protocol for Markov decision processes

- (i) $\mathcal{S} \in \mathbb{R}^{d_S}$ is the d_S -dimensional state space, i.e., the set of all possible observable states of the environment.
- (ii) $\mathcal{A} \in \mathbb{R}^{d_A}$ is the d_A -dimensional action space, i.e., the set of all possible actions that the agent can perform. Sometimes, not all the actions are performable in all states. In such cases, we can define the set $\mathcal{A}(s)$ for all $s \in \mathcal{S}$, such as $\mathcal{A} = \bigcup_{s \in \mathcal{S}} \mathcal{A}(s)$.
- (iii) $\mathcal{P} : \mathcal{S} \times \mathcal{A} \rightarrow \Delta(\mathcal{S})$ is a function called transition model such that, for every $s \in \mathcal{S}$ and $a \in \mathcal{A}$, it assigns a probability measure $\mathcal{P}(\cdot|s, a)$ over \mathcal{S} . In general, we denote with $\Delta(\mathcal{X})$ the set of probability measures over a measurable space \mathcal{X} ; The corresponding probability density function is $P(\cdot|s, a)$.
- (iv) $\mathcal{R} : \mathcal{S} \times \mathcal{A} \rightarrow \Delta[-R_{\max}, R_{\max}]$ is a bounded reward function such that, every time the agent chooses action $a \in \mathcal{A}$ in state $s \in \mathcal{S}$, it assigns a probability measure $\mathcal{R}(\cdot|s, a)$ over $[-R_{\max}, R_{\max}]$. With little abuse of notation, we will denote $\mathcal{R}(s, a)$ its expected return too. R_{\max} is the maximum absolute reward that the agent can receive, i.e., $\sup_{s, a} |\mathcal{R}(s, a)|$.
- (v) $\gamma \in (0, 1]$ is a discount factor to apply to future rewards. From an economical point of view, it accounts for the fact that an agent might be more interested in a pay-off obtained in the near future rather than a pay-off obtained far in the future. From a statistical point of view the discount factor is related to the probability that the process continues for another decision epoch.

(vi) $\mu \in \Delta(\mathcal{S})$ is the initial state distribution, such that the initial state is drawn as $s_0 \sim \mu$.

In the more general case, the state space \mathcal{S} and the action space \mathcal{A} , which are the sensor and actuator possibilities of the agent, respectively, can be both continuous and discrete, finite or infinite. In what follows, we will focus on the continuous case because it is the most relevant to our work. The time is typically modelled as a discrete sequence of decision steps represented by the natural numbers: $\mathcal{H} = \{0, 1, \dots, H\}$, where $H \in \mathbb{N}$ is the *horizon* of a given task, which can be either infinite ($H = \infty$) or finite. The agent-environment interaction ends when either the horizon is reached or a *terminal state* is reached, i.e., a state from which no other state can be reached. Tasks are called *episodic* when there exists a terminal state. After having reached a terminal state, usually all the rewards are considered to be zero. A *trajectory* is the sequence of states, actions and rewards $r_{h+1} \sim \mathcal{R}(\cdot|a_h, s_h)$ up to the last time step of the episode: $\tau = \{s_h, a_h, r_{h+1}\}_{h=0}^{H-1}$.

1.2.1 Policies

The core of a **MDP** agent is the *policy* π , a mapping from perceived states of the environment to possible actions.

Definition 1.2.2. (Policy) *A policy is a stochastic function $\pi : \mathcal{S} \rightarrow \Delta(\mathcal{A})$, such that the current action is drawn as $a \sim \pi(\cdot|s)$*

Hence, deterministic policies $\pi : \mathcal{S} \rightarrow \mathcal{A}$, such that the current action is prescribed as $a = \pi(s)$, are a particular case. As for bandits, in the most general case a policy takes as input the past history of states and actions, but in our work we only consider *memoryless policies*. In fact, we can always find an optimal policy that depends only on the current state. Moreover, we assumed that the agent's policy is stationary.

Remark 1.2.1. Note that we are adopting different notations for time steps in bandits and **MDPs**, t and h respectively. The reason is that we can think of a full **MDP** episode performed with policy π as a unique decision epoch t of a bandit. In other words, one could consider a bandit in which, at iteration t , the *bandit agent* pulls a policy π . The **MDP agent** perform a trajectory by interacting with its environment according to policy π . Then, the bandit agent obtains a reward

$r_t = \sum_{h=1}^H r_h$. This is the modelling approach that we will adopt in our work. For all details see Section (3.2).

1.2.2 Performance

As we stated above, the goal of an MDP agent is usually to maximize the total discounted reward, also called *return*:

$$\nu = \sum_{h=0}^{\infty} \gamma^h r_{h+1}, \quad (1.5)$$

where $\gamma \in (0, 1]$ is the discount rate. Given this objective, how can we evaluate the agent's policy? We need to design a *utility function* which represents the performance of the agent's policy with respect to its objective. There are two common formulations of the *performance* $J(\pi)$ in the reinforcement learning literature [120]. In the *start state formulation* the performance is calculated as the long-term discounted reward obtained by starting from a designated start state s_0 :

$$J(\pi) = \mathbb{E}[\nu \mid s_0 \sim \mu, \pi]. \quad (1.6)$$

Note that $\gamma = 1$ is allowed in episodic tasks only, otherwise the convergence of the performance is not guaranteed. We can now conveniently introduce the *stationary distribution of states under π* :

$$d^\pi(s) = (1 - \gamma) \sum_{h=0}^{\infty} \gamma^h \Pr(s_h = s \mid s_0 \sim \mu, \pi), \quad (1.7)$$

which is the probability induced by the policy π of having $s_h = s$, discounted by γ^h , when $t \rightarrow \infty$. This allows us to rewrite the performance measure as:

$$J(\pi) = \int_{\mathcal{S}} d^\pi(s) \int_{\mathcal{A}} \pi(a|s) \mathcal{R}(s, a) da ds. \quad (1.8)$$

In the *average reward formulation* policies are ranked according to their long-term expected reward per step:

$$\begin{aligned} J(\pi) &= \lim_{n \rightarrow \infty} \frac{1}{n} \mathbb{E} \left[\sum_{h=1}^n r_h \mid \pi \right] \\ &= \int_{\mathcal{S}} d^\pi(s) \int_{\mathcal{A}} \pi(a|s) \mathcal{R}(s, a) da ds, \end{aligned} \quad (1.9)$$

where $d^\pi(s) = \lim_{n \rightarrow \infty} \Pr(s_h = s \mid s_0 \sim \mu, \pi)$. In this work, we mostly adopt the first formulation of the performance utility function on episodic tasks, i.e., tasks with an absorbing (terminal) state.

1.2.3 Value functions

From the start state formulation of performance we can derive the value associated to a state s by following policy π , i.e., the *state-value function* $V^\pi(s) : \mathcal{S} \rightarrow \mathbb{R}$ defined recursively as:

$$V^\pi(s) = \mathbb{E}[\nu \mid s_0 = s, \pi] \quad (1.10)$$

$$= \int_{\mathcal{A}} \pi(a|s) \left(\mathcal{R}(s, a) + \gamma \int_{\mathcal{S}} P(s'|s, a) V^\pi(s') ds' \right) da, \quad (1.11)$$

which allows to re write the performance as:

$$J(\pi) = \int_{\mathcal{S}} \mu(s) V^\pi(s) ds. \quad (1.12)$$

Equation 1.11 is known as *Bellman's equation* of the state-value function. Thanks to another Bellman's equation we can define another value function, namely $Q^\pi : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$. This value function is more practical for control problems, in which we prefer to reason in terms of which actions are more valuable in a given state. Thus, we define the *action-value function* $Q^\pi(s, a)$ as:

$$\begin{aligned} Q^\pi(s, a) &= \mathbb{E}[\nu \mid s_0 = s, a_0 = a, \pi] \\ &= \mathcal{R}(s, a) + \gamma \int_{\mathcal{S}} P(s'|s, a) \int_{\mathcal{A}} \pi(a'|s') Q^\pi(s', a') da' ds', \end{aligned} \quad (1.13)$$

The difference between the two value functions is known as advantage function [15]:

$$A^\pi(s, a) = Q^\pi(s, a) - V^\pi(s) \quad (1.14)$$

Intuitively, the advantage function represents how much an action a is convenient in a state s w.r.t. the average utility of the actions.

Value functions are useful for evaluating the quality of a given policy or in order to define policies themselves. In fact, having an estimation of the value function for every state (and possibly action) one can build a policy following a greedy scheme. At each step we may choose the state-action pair that maximizes the action-value function, or an action that brings to the maximally valuable state among those that are reachable from the current state.

1.3 Reinforcement Learning

The most basic way to solve MDPs is *dynamic programming*, which simply consists in solving the Bellman equations presented in the previous chapter through a fixed-point iteration scheme. *Value iteration* and *Policy Iteration* are the most popular dynamic programming algorithms [119], which provide the basic structure for most of the value-based reinforcement learning methods. However, these algorithms suffer of two major problems. First, they require knowledge of the MDP transition kernel and of the reward function, which is not available in many real world problems. Second, the update involves an optimization with respect to all possible actions, which can be carried out efficiently only in the case of finite (small) action spaces. **Reinforcement Learning (RL)** is a subfield of Machine Learning which aims at solving large-scale problems where the dynamics of the MDP are not known, and thus dynamic programming algorithms can not be employed.

1.3.1 Problem formulation

RL is a branch of machine learning that aims at building learning agents capable to behave in a stochastic and possibly unknown environment, where the only feedback consists of a scalar reward signal. In order to maximize the long-run reward, the agent must learn which state-action pairs are the most profitable by

trial-and-error. Therefore, **RL** algorithms can be seen as computational methods to solve **MDPs** by directly interacting with the environment, for which a model may or may not be available. The **RL** problem can be formulated as a stochastic optimization problem aiming at finding the optimal policy π^* :

$$\pi^* = \arg \max_{\pi} J(\pi) \quad (1.15)$$

Remarkably, it is guaranteed that every **MDP** admits an optimal policy when the space of possible policies is unconstrained [100].

Trial-and-error search and a *delayed reward signal* can be seen as the most characteristic features of reinforcement learning. Compared to supervised learning, one of the main branches of machine learning, the feedback the learner receives is usually less frequent and can be very sparse. In supervised learning, the agent is provided with examples of the correct or expected behaviour by a knowledgeable external supervisor and the agent's goal is to learn how to replicate these examples as well as possible, and possibly generalize this knowledge to new examples. In reinforcement learning, the agent receives a numerical reward that only represents a partial feedback about the goodness of actions taken. A feedback system of this sort is said to be *evaluative* rather than *instructive* and it makes it much more difficult for the agent to learn how to behave in uncharted territory. Evidently, the exploration-exploitation trade-off is a substantial problem in **RL** as much as for bandits. An agent must exploit what is known of the environment and the reward function in order to obtain rewards, but it also needs to explore to select better actions in the future. On top of this, since rewards might be delayed in time, it will be difficult for the agent to understand which actions are mostly responsible for the received outcome. This represents another characteristic problem of reinforcement learning known as *credit assignment problem* [119]. As we will see, **RL** algorithms are based on two key ideas: the first is to use samples to derive an approximate representation of the unknown dynamics of the controlled system. The second idea is to use function approximation methods to estimate value functions and policies in high-dimensional state and action spaces.

1.3.2 Taxonomy

Along the years, many algorithms have been proposed to solve the **RL** problem as presented above. The solutions proposed often display similar approaches

that can be used to outline a rough taxonomy of the [RL](#) algorithms. In our taxonomy we consider the algorithms along four dimensions: *model requirements*, *policy-based sampling strategy*, *solution search*, *sample usage*. The first dimension refers to the requirements of the algorithm w.r.t. the model of the [MDP](#). On the two sides of this dimension we have:

- *Model-based* algorithms, which require an explicit approximation of the model of the [MDP](#). Not every model-based algorithm is equally demanding on this matter: some of them might need information about every element of the [MDP](#) (transition model, reward model, initial state distribution, etc.) while others might require approximations only for a fraction of them, e.g., the reward model only. Examples: DYNA [118], contextual policy-search[67].
- *Model-free* algorithms, on the other hand, do not require any explicit approximation of the model. Model-free algorithms usually have low computational demands but require lots of data in order to get good results; they are well-suited for problems in which computation is costly but sampling is cheap. Examples: Q-learning [128], SARSA [103], REINFORCE [132].

The *policy-based sampling strategy* dimension refers to the relation between the policy that is being used to interact with the environment (*behavioural policy*) and the policy that is being learned by the agent (*target policy*);

- in *off-policy* algorithms there is a clear distinction between the behavioural policy, the one which collects samples and explore the environment, and target policy, which is learned independently. This approach is often useful to safely improve exploration but it is usually more cumbersome to analyse theoretically. Examples: Q-learning [128], off-policy actor-critic [41].
- in *on-policy* algorithms there is no distinction between target and behavioural policy. Examples: SARSA [103], TD $\{\lambda\}$ [117].

The *solution search-space* dimension refers to the space where the optimal solution is searched:

- in direct *policy search* methods the optimal solution is searched in the space of policies, e.g., the space in which their parameters lie. These methods

are well-suited for large state or action spaces, produce smooth changes in the policy during the learning process, and allow to introduce prior expert knowledge in the policy; unfortunately, they often suffer from a high variance and have optimization issues. Examples: REINFORCE [132], G(PO)MDP [16].

- *Value-based* methods rely instead on the computation of the value function to learn the optimal policy indirectly. Value-based techniques have good convergence properties under small state and action spaces and turn out very suitable when there is insufficient or none prior knowledge about the problem. However, changes to the underlying policy during the learning process can be unstable, and the convergence properties disappear when large (e.g., continuous) state and action spaces demand the use of function approximation. Examples: value-iteration [119], FQI [7].

Differently from the other dimensions which are populated by sharp dichotomies, policy and value-based methods can be combined, often with very successful results. For example, *actor-critic* methods [49] look for the optimal policy in the policy parameter space while leveraging on the predictive power of value-functions in order to guide the parameters update.

The fourth dimension of the taxonomy is the *update frequency*, which refers to the degree of interleaving between learning and experience. Along this dimension, we distinguish:

- *continuing* algorithms, which update the policy (directly or indirectly through the value function) every time new information is available, possibly at each time step;
- *episodic* algorithms, which divides experience into finite segments, called episodes, and update the policy in between each episode;
- *batch* algorithms, which divide learning and experience in two distinct phases. Typically, these are off-policy methods in which a set of behavioural policies collects the data and the target policy is updated upon completion of the batch.

A finer classification of this dimension is presented in [70], where the authors remark that the distinctions between the categories does not depend on the actual formulation: almost any algorithm can fall in any of these three categories depending on the implementation.

1.4 Policy Search

As mentioned in the introduction, this work focuses on improving the exploration task in continuous state-action domains, possibly characterized by some noise in the state as it happens for control tasks with noisy sensors. In such conditions, value-based methods present numerous difficulties. First, they have no guarantees of convergence to an optimal policy due to the need of function approximation for large, continuous MDPs; second, value based methods are highly sensitive to small perturbations in the state, which makes them useless in noisy control tasks. Hence, direct Policy Search (PS) methods represent the best alternative in such settings. Theoretical guarantees are often available [82], environment noise has less impactful effects, and prior domain knowledge can be exploited to design ad-hoc policies for specific tasks. Moreover, approximate value functions can still be used to guide the search for the optimal policy, such as in actor-critic methods. Indeed, PS has been successfully applied to complex control tasks, as reported in [42]: from robotic arms playing baseball to simulated table tennis, from dart throwing to pan-cake flipping.

1.4.1 Overview

Given a predetermined class of policies $\hat{\Pi}$, PS aims at finding the policy whose performance $J(\pi)$ is as close as possible to the performance of the optimal policy $J(\pi^*) = J^*$:

$$\hat{\pi} = \arg \min_{\pi \in \hat{\Pi}} \|J^* - J(\pi)\|_p. \quad (1.16)$$

When $p = 2$, this optimization problem can be interpreted as finding the policy $\hat{\pi} \in \hat{\Pi}$ whose orthogonal projection in the space of Markovian stationary policies Π coincides with the optimal policy π^* .

A Variety of technique have been proposed in literature to solve the problem defined by Equation (1.16). As well as for value-based methods, we can distinguish between model-free, which learn policies directly based on sampled trajectories, and model-based approaches, which use the sampled trajectories to first build a model of the state dynamics. A part from this macro distinction, a further classification can be based on whether we predict trajectories deterministically or generate them stochastically by sampling. In the case of *stochastic trajectory*

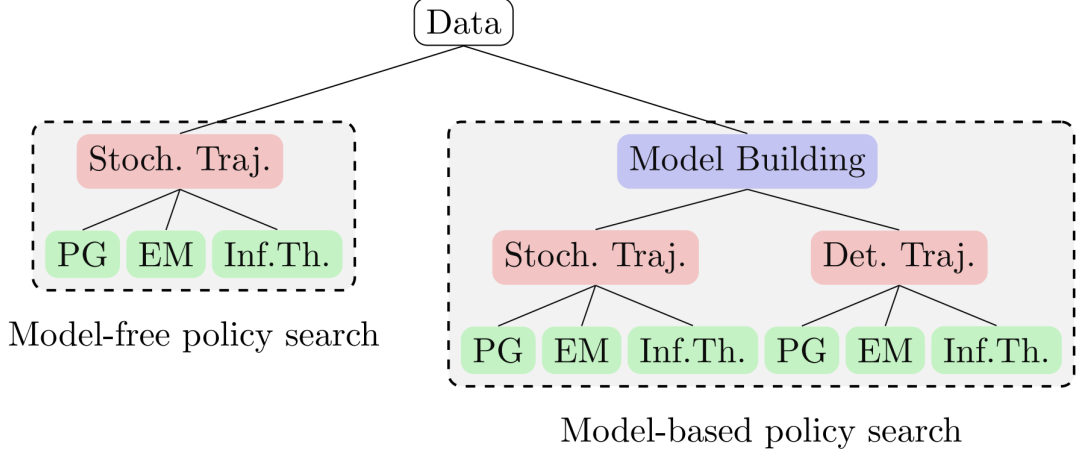


Figure 1.2: A taxonomy of PS methods [42]

generation, trajectories are sampled from the interaction of the agent with the environment, or a simulation of it. *Deterministic trajectory prediction* does not sample trajectories, but analytically predicts the trajectory distribution $p_{\theta}(\tau)$. Typically, deterministic trajectory prediction is computationally more involved than sampling trajectories from the system. However, for the subsequent policy update, deterministic trajectory prediction can allow for an analytic computation of gradients, which can be advantageous over stochastic trajectory generation, where these gradients can only be approximated. Moreover, we can classify policy search methods according to their policy update strategies, as depicted in Figure (1.2). The policy updates in both model-free and model-based PS are based on either policy gradients **Policy Gradient (PG)** [120], expectation-maximization-based updates [40, 65], or information-theoretic insights [114]. In the followings, we will focus on model-free PS with PG updates.

1.4.2 Policy gradient

In the context of model-free PG, the agent's behaviour is modelled as a differentiable parametric policy $\pi_{\theta} : \mathcal{S} \rightarrow \Delta(\mathcal{A})$, independent of time (*stationary*), such that the current action is drawn as $a_h \sim \pi_{\theta}(\cdot | s_h) = \pi(\cdot | s_h, \theta)$, where $\theta \in \Theta \subseteq \mathbb{R}^m$ are the policy parameters. The most simple parametrization one could think of is the linear one, where the policy only depends linearly on the policy parameters and the action is drawn deterministically:

$$a = \pi_{\theta}(s) = \theta^T \phi(s), \quad (1.17)$$

where $\phi(s)$ can be any state feature function. In stochastic formulations, typically, a zero-mean Gaussian noise vector is added to $\pi_{\theta}(s)$, so that the policy becomes:

$$\pi_{\theta}(a|s) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2}\left(\frac{a - \theta^T \phi(s)}{\sigma}\right)^2\right). \quad (1.18)$$

In some cases, the covariance matrix is learnable too, and the parameter set becomes $\{\theta; \Sigma\}$. In most cases, Σ is diagonal, thus easing the complexity of the learning task along with the theoretical analysis. Hence, Problem (1.16) translates into finding the optimal policy parameters:

$$\theta^* = \arg \max_{\theta \in \Theta} J(\theta). \quad (1.19)$$

This new optimization problem can be solved by resorting to gradient ascent on the policy parameters, which is guaranteed to converge to a local optimum at least:

$$\theta^{t+1} \leftarrow \theta^t + \alpha \mathbf{G}^{-1}(\theta^t) \nabla_{\theta} J(\theta^t), \quad (1.20)$$

where $\alpha \geq 0$ is the *learning rate*, or *step size*, and $\mathbf{G}(\theta)$ is a positive definite matrix, called *preconditioning matrix*. The quantity $\nabla_{\theta} J(\theta)$ denotes the *policy gradient* PG which gives the name to this method. Its expression is derived in [120].

Theorem 1.4.1. Policy Gradient Theorem *Given a MDP \mathcal{M} and a Markovian stationary stochastic parametric policy π_{θ} differentiable w.r.t. to θ for all state-action pairs $(s, a) \in (\mathcal{S}, \mathcal{A})$, the gradient of the policy performance is given by:*

$$\nabla_{\theta} J(\theta) = \int_{\mathcal{S}} d^{\pi_{\theta}}(s) \int_{\mathcal{A}} \nabla_{\theta} \pi_{\theta}(a|s) Q^{\pi_{\theta}}(s, a) da ds$$

$\pi_{\theta}(s)$ is the stationary state distribution induced by policy π_{θ} , as defined in Equation (1.7). By applying a trivial differentiation rule, $\nabla \log f = \nabla f / f$, we can rewrite Equation (1.21) in a way that will turn out extremely useful:

$$\begin{aligned}
\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) &= \int_{\mathcal{S}} d^{\pi_{\boldsymbol{\theta}}}(s) \int_{\mathcal{A}} \pi_{\boldsymbol{\theta}} \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a|s) Q^{\pi_{\boldsymbol{\theta}}}(s, a) da ds \\
&= \mathbb{E}_{s \sim d^{\pi_{\boldsymbol{\theta}}}, a \sim \pi_{\boldsymbol{\theta}}(\cdot|s)} [\nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a|s) Q^{\pi_{\boldsymbol{\theta}}}(s, a)].
\end{aligned} \tag{1.21}$$

This rephrasing is known as the REINFORCE trick [132] and gives the name to an algorithm which is a milestone of **RL**. In practical applications it can be inconvenient or impossible to compute the Q-function. One solution is to leverage simple function approximators belonging to the class of *compatible basis functions*, i.e., functions of the form $f_{\boldsymbol{\omega}} = \boldsymbol{\omega}^T \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a|s)$. Such approximators can replace $Q^{\pi_{\boldsymbol{\theta}}}(s, a)$ in Equation (1.21) for the calculation of the policy gradient as proven in [120].

A second solution that prevent from calculating $Q^{\pi_{\boldsymbol{\theta}}}(s, a)$ explicitly is to resort to a trajectory-based reformulation of Equation (1.21). By rephrasing the expected performance under policy $\pi_{\boldsymbol{\theta}}$ defined in Equation (1.6) as:

$$J(\boldsymbol{\theta}) = \mathbb{E}_{\tau \sim p_{\boldsymbol{\theta}}} [\mathcal{R}(\tau)], \tag{1.22}$$

where $p_{\boldsymbol{\theta}}$ is the distribution over trajectories $\tau \in \mathcal{T}$ induced by the policy $\pi_{\boldsymbol{\theta}}$, and $\mathcal{R}(\tau) = \sum_{h=0}^{H-1} \gamma^h r_{h+1}$, we can write:

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \int_{\mathcal{T}} \nabla_{\boldsymbol{\theta}} p_{\boldsymbol{\theta}}(\tau) \mathcal{R}(\tau) d\tau \tag{1.23}$$

$$= \mathbb{E}_{\tau \sim p_{\boldsymbol{\theta}}} [\nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\tau) \mathcal{R}(\tau)] \tag{1.24}$$

This formulation of the **PG** turns out to be extremely practical. Not only because it prevents from the calculation of the Q-function, but also because it does not require any knowledge about the transition kernel of the **MDP**. In fact, $\log p_{\boldsymbol{\theta}}(\tau)$ can be easily derived from the sheer knowledge of the trajectory and definition of the policy:

$$\nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\tau) = \nabla_{\boldsymbol{\theta}} \log \left(\mu(s_{\tau,0}) \prod_{t=0}^{H-1} \pi_{\boldsymbol{\theta}}(a_{\tau,h}|s_{\tau,h}) P(a_{\tau,h+1}|s_{\tau,h+1}) \right) \tag{1.25}$$

$$= \sum_{h=0}^{H-1} \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a_{\tau,h}|s_{\tau,h}), \quad \forall \tau \in \mathcal{T} \tag{1.26}$$

At this point, the careful reader might have noticed that we have not yet discussed the meaning of the $\mathbf{G}(\boldsymbol{\theta})$ in the parameters update Equation (1.20). The choice of this matrix represent the direction we want to take when performing a gradient update. The two most common direction choices in the RL literature are *steepest gradient ascent* and *natural gradient ascent*. In the first case, it is sufficient to set $\mathbf{G}(\boldsymbol{\theta}) = \mathbf{I}$. However, this option might be ineffective in many cases [6]:

- when there are large plateaus where the gradient is very small and does not point in the direction of the global optimum;
- when the performance function (or, in general, the loss function to optimize) is multimodal;
- when the gradient is not isotropic in magnitude w.r.t. any direction away from its maximum, creating troubles in the step size tuning.

In such cases, the *natural gradient* has been empirically proven to have faster convergence and to avoid premature convergence to local maxima. Natural gradient considers the parameter space as a Riemann manifold equipped with its own norm $\|\boldsymbol{\theta}\|_{\mathbf{G}(\boldsymbol{\theta})}^2 = \boldsymbol{\theta}^T \mathbf{G}(\boldsymbol{\theta}) \boldsymbol{\theta}$, which replaces the Euclidean norm, $\|\boldsymbol{\theta}\|_{\mathbf{I}}^2 = \boldsymbol{\theta}^T \boldsymbol{\theta}$. Such parametric space is a Riemann manifold whose points are probability measures defined on a common probability space. Since \mathbf{G} represents the local Riemann metric tensor, in this context it is given by the *Fisher Information Matrix*, i.e., $\mathbf{G}(\boldsymbol{\theta}) = \mathbf{F}(\boldsymbol{\theta})$:

$$\mathbf{F}(\boldsymbol{\theta}) = \mathbb{E}_{\tau \sim p_{\boldsymbol{\theta}}} [\nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\tau) \nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\tau)^T]. \quad (1.27)$$

For more details on the advantages of the natural gradient over the steepest ascent gradient we refer to [6, 5, 98].

We are now ready to present the general setup for policy gradient methods, showed in Algorithm (1.2).

1.4.3 Policy gradient estimation

As shown in the generic policy gradient algorithm, at each iteration an estimate of the policy gradient is required. Indeed, finding a good estimator is one of the main

Algorithm 1.2 Generic PG algorithm

-
- 1: **Input:** initial policy parameters θ^0 , learning rate α
 - 2: **Initialize** $t = 0$
 - 3: **while** not converged **do**
 - 4: Estimate $G(\theta^t)$ with an estimator $\hat{G}(\theta^t)$
 - 5: Estimate $\nabla_{\theta} J(\theta^t)$ with an estimator $\hat{\nabla}_{\theta} J(\theta^t)$
 - 6: Update the policy parameters $\theta^{t+1} \leftarrow \theta^t + \alpha \hat{G}^{-1}(\theta^t) \hat{\nabla}_{\theta} J(\theta^t)$
 - 7: $t = t + 1$
 - 8: **end while**
 - 9: **return** an approximation of the optimal policy parameters θ^*
-

challenges of policy gradient methods. Since *RL* aims at solving *MDPs* whose model is unknown to the agent, the sole mean to estimate the policy gradient is by leveraging on the experience collected, i.e., the samples. Among several techniques proposed in the literature over the last years, the most prominent approaches to estimate the policy gradient from samples are *Finite-Difference* and *Likelihood Ratio* methods [48].

Finite differences

Finite difference methods aim at approximating the policy gradient as a quotient of finite increments. The idea is to perform multiple perturbations $\Delta\theta_1, \Delta\theta_2, \dots, \Delta\theta_N$ of the policy parameters. Then, with each set of perturbed parameters collect a number of sample trajectories in order to calculate $\Delta\hat{J}_i = J(\theta + \Delta\theta_i) - J(\theta)$. At this point, the policy gradient can be estimated by regression as:

$$\hat{\nabla}_{\theta} J(\theta) = (\Delta\Theta^T \Delta\Theta)^{-1} \Delta\hat{J}, \quad (1.28)$$

where $\Delta\Theta = [\Delta\theta_1, \Delta\theta_2, \dots, \Delta\theta_N]$ and $\Delta\hat{J} = [\Delta\hat{J}_1, \Delta\hat{J}_2, \dots, \Delta\hat{J}_N]$. This method is easy to implement and very efficient when applied to deterministic tasks or pseudo-random number simulations. However, it becomes useless in real control tasks, where a large number of trajectories is required and noise slows down convergence. Moreover, the choice of the perturbation of the parameters is a very difficult problem which may cause instability. For these reasons, the likelihood-ratio method is largely preferred in real control tasks.

Likelihood ratio

Likelihood ratio methods were among the first policy search methods introduced in the early 1990s by Williams [132], and include the famous REINFORCE

algorithm. These methods build upon the policy gradient formulation given by Equation (1.24), which, in the same way of Equation (1.21), has been rewritten by applying the so called *REINFORCE trick*, also called *likelihood ratio trick*. As we have seen in Equation (1.26), the policy gradient (Equation (1.24)) can be approximated by using a sum over the sampled trajectories. In a similar way, we can estimate $\mathcal{R}(\tau)$ in a Monte-Carlo fashion. However, such estimates suffer of very large variance. The variance can be reduced by introducing a baseline b for the trajectory reward $\mathcal{R}(\tau)$, i.e.,

$$\hat{\nabla}_{\boldsymbol{\theta}} J(\boldsymbol{\theta}, b) = \mathbb{E}_{\tau \sim p_{\boldsymbol{\theta}}} [\nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\tau) (\mathcal{R}(\tau) - b)] \quad (1.29)$$

Remarkably, adding the baseline keep the estimator unbiased. The baseline can be chosen arbitrarily in order to minimize the variance, with the sole condition of being action-independent. The variance-minimizing baseline is usually referred to as *optimal baseline*. Clearly, the optimal baseline depends on the specific likelihood gradient estimation adopted.

1.4.4 Algorithms

The most popular sample-based estimate of the gradient is undoubtedly REINFORCE [132], which uses the total return directly:

$$\hat{\nabla}_{\boldsymbol{\theta}} J(\boldsymbol{\theta}, b)_{RF} = \frac{1}{N} \sum_{i=1}^N \left(\sum_{h=0}^{H-1} \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a_{\tau_i, h} | s_{\tau_i, h}) \right) \left(\sum_{h=0}^{H-1} \gamma^h r_{\tau_i}^{h+1} - b \right), \quad (1.30)$$

based on N independent trajectories. The variance of such estimator is represented by a $m \times m$ covariance matrix, with m equals the number of parameters of the policy. We can obtain an optimal baseline in two ways. Either we minimize each element of the diagonal, obtaining a component-wise baseline made of m elements [98]. Or we can minimize the trace of the covariance matrix, obtaining a scalar baseline [134]:

Algorithm 1.3 Episodic REINFORCE with component-wise optimal baseline.

- 1: **Input:** policy parametrization θ
- 2: **Initialize:** $n = 0$
- 3: **while** not converged **do**
- 4: collect a trajectory τ_n
- 5: **for** every gradient component $j = 1, 2, \dots, m$ **do**
- 6: Estimate the optimal baseline

$$b_j^n = \frac{\sum_{i=1}^n \left(\sum_{h=0}^{H-1} \nabla_{\theta} \log \pi_{\theta}(a_{\tau_i, h} | s_{\tau_i, h}) \right)^2 \left(\sum_{h=0}^{H-1} \gamma^h r_{\tau_i}^{h+1} \right)}{\sum_{i=1}^n \left(\sum_{h=0}^{H-1} \nabla_{\theta} \log \pi_{\theta}(a_{\tau_i, h} | s_{\tau_i, h}) \right)^2}$$

- 7: Estimate the gradient element

$$\hat{\nabla}_{\theta_j} J(\theta)^n = \frac{1}{n} \sum_{i=1}^n \left(\sum_{h=0}^{H-1} \nabla_{\theta_j} \log \pi_{\theta}(a_{\tau_i, h} | s_{\tau_i, h}) \right) \left(\sum_{h=0}^{H-1} \gamma^h r_{\tau_i}^{h+1} - b_j^n \right)$$

- 8: **end for**
 - 9: $n = n + 1$
 - 10: **end while**
 - 11: **return** gradient estimate $\hat{\nabla}_{\theta_j} J(\theta)^N$
-

$$(b_{RF}^*)_j = \frac{\mathbb{E}_{\tau \sim p_{\theta}} \left[\left(\sum_{h=0}^{H-1} \nabla_{\theta} \log \pi_{\theta}(a_{\tau, h} | s_{\tau, h}) \right)^2 \mathcal{R}(\tau) \right]}{\mathbb{E}_{\tau \sim p_{\theta}} \left[\left(\sum_{h=0}^{H-1} \nabla_{\theta} \log \pi_{\theta}(a_{\tau, h} | s_{\tau, h}) \right)^2 \right]}, \quad j = 1, 2, \dots, m; \quad (1.31)$$

$$b_{RF}^* = \frac{\mathbb{E}_{\tau \sim p_{\theta}} \left[\left\| \sum_{h=0}^{H-1} \nabla_{\theta} \log \pi_{\theta}(a_{\tau, h} | s_{\tau, h}) \right\|_2^2 \mathcal{R}(\tau) \right]}{\mathbb{E}_{\tau \sim p_{\theta}} \left[\left\| \sum_{h=0}^{H-1} \nabla_{\theta} \log \pi_{\theta}(a_{\tau, h} | s_{\tau, h}) \right\|_2^2 \right]}. \quad (1.32)$$

As for the REINFORCE estimator (1.30), these optimal baselines are estimated simply by replacing the expectation with the empirical average. Algorithm (1.3) shows the full REINFORCE procedure with component-based optimal baseline estimation. For sake of clarity, we underline that this algorithm, as well as the others that we discuss in this section, is meant to carry out step (5) of the generic policy gradient algorithm, i.e., Algorithm (1.2).

Another solution tackling the high-variance problem of REINFORCE is to leverage on the intuitive observation that future actions do not depend on past

rewards (unless policy changes take place continuously along the trajectory). Hence, we can derive two other well-know gradient estimators, [Gradient of the average reward in Partially Observable MDPs \(GPOMDP\)](#) [16] and [PGT](#) [120]:

$$\hat{\nabla}_{\boldsymbol{\theta}} J(\boldsymbol{\theta}, b)_{GPOMDP} = \frac{1}{N} \sum_{i=1}^N \left(\sum_{h=0}^{H-1} \left(\sum_{h'=0}^h \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a_{\tau_i, h'} | s_{\tau_i, h'}) \right) (\gamma^h r_{\tau_i}^{h+1} - b_h) \right), \quad (1.33)$$

$$\hat{\nabla}_{\boldsymbol{\theta}} J(\boldsymbol{\theta}, b)_{PGT} = \frac{1}{N} \sum_{i=1}^N \left(\sum_{h=0}^{H-1} \gamma^h \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a_{\tau_i, h} | s_{\tau_i, h}) \left(\sum_{h'=h}^{H-1} \gamma^{h'-h} r_{\tau_i}^{h'+1} - b_h \right) \right). \quad (1.34)$$

In [98] the authors show that these two estimators are equivalent, despite their apparent difference. In the same paper, the authors show how to derive the optimal baseline for [GPOMDP](#), which, differently from the REINFORCE case, can be time dependent. In the case $b = 0$ and under mild assumptions, this gradient estimation has been proven to suffer from less variance than REINFORCE [134]. However, large variance remains a common trait of these Monte Carlo [PG](#) techniques. In fact, being trajectories generated by sampling at each time step according to a stochastic policy $\pi_{\boldsymbol{\theta}}$, the estimators inherit the variance of the policy. To address this issue, in [110] the authors propose the [Policy Gradient with Parameter-Based Exploration \(PGPE\)](#) method, in which the search in the policy space is replaced with a direct search in the model parameter space. This allows the use of a deterministic controller $\pi_{\boldsymbol{\theta}} : \boldsymbol{\theta} \in \Theta \subseteq \mathbb{R}^m$ for sampling the trajectories, i.e., $\pi_{\boldsymbol{\theta}}(a|s) = \delta(a - v_{\boldsymbol{\theta}}(s))$, where $v_{\boldsymbol{\theta}}$ is a deterministic function of the state s , e.g., [111]. The policy parameters are sampled from a distribution $\nu_{\boldsymbol{\xi}} \in \delta(\Theta)$, called *hyper-policy*, where $\boldsymbol{\xi} \in \Xi \subseteq \mathbb{R}^d$ are the hyper-policy parameters, or *hyper-parameters*. Thus, in episodic [PGPE](#) it is sufficient to sample the parameters $\boldsymbol{\theta} \sim \nu_{\boldsymbol{\xi}}$ once at the beginning of the episode and then generate an entire trajectory following the deterministic policy $\pi_{\boldsymbol{\theta}}$, with a consequent reduction of the gradient estimate variance. As an additional benefit, the parameter gradient is estimated by direct parameter perturbations, without having to back-propagate any derivatives, which allows to use non-differentiable controllers. For what concern the hyper-policy parametrization choice, the most typical one is Gaussian with diagonal covariance matrix, as it happens in classical [PG](#). Although the policy is deterministic, the exploration is guaranteed by the stochasticity of the

Algorithm 1.4 Episodic PGPE

-
- 1: **Input:** initial hyper-parameters ξ^0 , learning rate α
 - 2: **Initialize** $t = 0$
 - 3: **while** not converged **do**
 - 4: **for** $n = 1, 2, \dots, N$ **do**
 - 5: Sample controller parameters $\theta^{(n)} \sim \nu_{\xi_t}$
 - 6: Sample trajectory $\tau \sim p_{\theta}$ under policy π_{θ}
 - 7: **end for**
 - 8: Estimate optimal baseline b
 - 9: Estimate the hyper-policy gradient:

$$\hat{\nabla}_{\xi} J(\xi_t) = \frac{1}{N} \sum_{i=1}^N \nabla_{\xi} \log \nu_{\xi}(\theta^{(i)}) (\mathcal{R}(\tau^{(i)}) - b)$$

- 10: Update the hyper-parameters $\xi_{t+1} = \xi_t + \alpha \hat{\nabla}_{\xi} J(\xi_t)$
 - 11: $t = t + 1$
 - 12: **end while**
 - 13: **return** an approximation of the optimal policy parameters $\theta^* \sim \nu_{\xi^*}$
-

hyper-policy. The hyper-parameters ξ are updated by following the gradient ascent direction of the gradient of the expected reward, which can be rewritten as:

$$J(\xi) = \int_{\Theta} \int_{\mathcal{T}} \nu_{\xi}(\theta) p_{\theta}(\tau) \mathcal{R}(\tau) d\tau d\theta, \quad (1.35)$$

where $\nu_{\xi}(\theta) p_{\theta}(\tau) = p_{\xi}(\theta, \tau)$ because τ is conditionally independent from ξ given θ . Applying the likelihood ratio technique, we obtain:

$$\nabla_{\xi} J(\xi) = \mathbb{E}_{\theta \sim \nu_{\xi}, \tau \sim p_{\theta}} [\nabla_{\xi} \log \nu_{\xi}(\theta) \mathcal{R}(\tau)] \quad (1.36)$$

In order to further reduce the estimate variance, we can adopt an estimator with baseline and compute the optimal one similarly to the REINFORCE case. The episodic PGPE algorithm is reported in Algorithm 1.4.

1.5 Multiple Importance Sampling

In the last section of this chapter we present a statistical tool which is an extension of the well known *importance sampling*. Although this is not strictly related to learning itself, we introduce this tool to the reader because our work leverages it to enable off-line learning for the agent, in a way that is described thoroughly in Chapter (3). We conclude this section with a lemma which represents the first little contribution of this work to the literature and an essential building block for further developments.

Importance sampling [36, 94] is a technique that allows estimating the expectation of a function under some *target* or *proposal* distribution with samples drawn from a different distribution, called *behavioral*. Let P and Q be probability measures on a measurable space $(\mathcal{Z}, \mathcal{F})$, such that $P \ll Q$ (i.e., P is absolutely continuous w.r.t. Q). The importance weight $w_{P/Q}$ is the Radon-Nikodym derivative of P w.r.t. Q , i.e., $w_{P/Q} \equiv \frac{dP}{dQ}$. Let p and q be the densities of P and Q , respectively, w.r.t. a reference measure. From the chain rule, $w_{P/Q} = \frac{p}{q}$. In the continuous case, p and q are probability density functions of absolutely continuous random variables having laws P and Q , respectively, and $w_{P/Q}$ is a likelihood ratio. Given a bounded function $f : \mathcal{Z} \rightarrow \mathbb{R}$, and a set of i.i.d. outcomes z_1, \dots, z_N sampled from Q , the importance sampling estimator of $\mu := \mathbb{E}_{z \sim P} [f(z)]$ is:

$$\hat{\mu}_{\text{IS}} = \frac{1}{N} \sum_{i=1}^N f(z_i) w_{P/Q}(z_i), \quad (1.37)$$

which is an *unbiased* estimator [94], i.e., $\mathbb{E}_{z_i \stackrel{\text{iid}}{\sim} Q} [\hat{\mu}_{\text{IS}}] = \mu$.

Multiple Importance Sampling (MIS) [126] is a generalization of the importance sampling technique which allows samples drawn from several different behavioral distributions to be used for the same estimate. Let Q_1, \dots, Q_K be all probability measures over the same probability space as P , and $P \ll Q_k$ for $k = 1, \dots, K$. Let $\beta_1(z), \dots, \beta_K(z)$ be mixture weights, i.e., for all $z \in \mathcal{Z}$, $\beta_1(z) + \dots + \beta_K(z) = 1$ and $\beta_k(z) \geq 0$ for $k = 1, \dots, K$. Let z_{ik} denote the i -th sample drawn from Q_k . Given N_k i.i.d. samples from each Q_k , the **MIS** estimator is:

$$\hat{\mu}_{\text{MIS}} = \sum_{k=1}^K \frac{1}{N_k} \sum_{i=1}^{N_k} \beta_k(z_{ik}) w_{P/Q_k}(z_{ik}) f(z_{ik}), \quad (1.38)$$

which is also an unbiased estimator of μ for any valid choice of the mixture weights. A common choice of the mixture weights having desirable variance

properties is the balance heuristic [126]:

$$\beta_k(z) = \frac{N_k q_k(z)}{\sum_{j=1}^K N_j q_j(z)}, \quad (1.39)$$

which yields the **Balance Heuristic Estimator (BH)**:

$$\hat{\mu}_{\text{BH}} = \sum_{k=1}^K \sum_{i=1}^{N_k} \frac{p(z_{ik})}{\sum_{j=1}^K N_j q_j(z_{ik})} f(z_{ik}). \quad (1.40)$$

Since (1.39) are valid mixture weights, $\hat{\mu}_{\text{BH}}$ is an unbiased estimator of μ . Moreover, its variance is not significantly larger than any other choice of the mixture weights [126]. An appealing interpretation of the balance heuristic is that we can look at $\hat{\mu}_{\text{BH}}$ as an importance sampling estimation in which samples are drawn from the mixture $\Phi = \frac{p(z_{ik})}{\sum_{j=1}^K \frac{N_j}{N} q_j(z_{ik})}$.

To further characterize the variance of this estimator, we introduce the concept of *Rényi divergence*. Given probability measures P and Q on $(\mathcal{Z}, \mathcal{F})$, where $P \ll Q$ and Q is σ -finite, the α -Rényi divergence is defined as [101]:

$$D_\alpha(P\|Q) = \frac{1}{\alpha - 1} \log \int_{\mathcal{Z}} (w_{P/Q})^\alpha dQ, \quad (1.41)$$

for $\alpha \in [0, \infty]^1$. We denote the *exponentiated α -Rényi divergence* with:

$$d_\alpha(P\|Q) = \exp\{D_\alpha(P\|Q)\}. \quad (1.42)$$

Of particular interest is d_2 , as the variance of the importance weight is $\text{Var}_{z \sim Q} [w_{P/Q}(z)] = d_2(P\|Q) - 1$, which is a divergence itself [37]. For this reason, we always mean the 2-Rényi divergence when omitting the order α . The Rényi divergence was used by [80] to upper bound the variance of the importance sampling estimator as:

$$\text{Var}_{z_i \stackrel{\text{iid}}{\sim} Q} [\hat{\mu}_{\text{IS}}] \leq \|f\|_\infty^2 d_2(P\|Q)/N. \quad (1.43)$$

A similar result can be derived for the BH estimator:

Lemma 1.5.1. *Let P and $\{Q_k\}_{k=1}^K$ be probability measures on the measurable space $(\mathcal{Z}, \mathcal{F})$ such that $P \ll Q_k$ and $d_2(P\|Q_k) < \infty$ for $k = 1, \dots, K$. Let*

¹The special cases $\alpha = 0, 1$ and ∞ are defined as limits.

$f : \mathcal{Z} \rightarrow \mathbb{R}$ be a bounded function, i.e., $\|f\|_\infty < \infty$. Let $\hat{\mu}_{BH}$ be the balance heuristic estimator of f , as defined in (1.40), using N_k i.i.d. samples from each Q_k . Then, the variance of $\hat{\mu}_{BH}$ can be upper bounded as:

$$\mathbb{V}\text{ar}_{z_{ik} \sim Q_k} [\hat{\mu}_{BH}] \leq \|f\|_\infty^2 \frac{d_2(P\|\Phi)}{N}, \quad (1.44)$$

where $N = \sum_{k=1}^K N_k$ is the total number of samples and $\Phi = \sum_{k=1}^K \frac{N_k}{N} Q_k$ is a finite mixture.

Chapter 2

Exploration Techniques

In this chapter we present the state of the art of [MABs](#) and [RL](#) techniques that focus on the exploration challenge arising in these learning frameworks. While sketching a sort of taxonomy of the exploration techniques, we describe some emblematic algorithms for each category, with particular attention to those that inspired our work. Indeed, the exploration problem in the [PS](#) setting is the main target of our thesis project. Our main contributions, described in Chapters (3-4), have been designed after a careful literature review. In this chapter we try to report the most relevant insights collected along this review. The reader may notice that, despite this thesis project aims at solving the exploration problem in the framework of [PS](#), few references to [PS](#) algorithms will be given. In fact, to the best of our knowledge, little research has been done so far on the exploration problem in [PS](#).

Following the taxonomy outlined by Sebastian Thrun in 1992 for the [RL](#) framework [123], we divide both [MABs](#) and [RL](#) exploration techniques in two families of exploration schemes: *undirected* and *directed* exploration. While the former family is closely related to random walk exploration, directed exploration techniques memorize exploration-specific knowledge which is used for guiding the exploration search. In many finite deterministic domains, any learning technique based on undirected exploration is inefficient in terms of learning time, i.e. learning time is expected to scale exponentially with the size of the state space [130]. For all these domains, reinforcement learning using a directed technique can always be performed in polynomial time, demonstrating the important role of exploration in reinforcement learning [123]. However, an important remark is that we do not address the problem of pure exploration, in which there is no price to be paid for exploration and the only objective is to find the reward-maximizing

actions. Instead, we investigate effective exploration in the more general context of learning described in the previous chapter (1.1.1), where the agent faces the exploration-exploitation dilemma all along its journey. How can the agent achieve a better balance between exploration and exploitation? How can it explore more effectively? Can it improve the effectiveness of its exploration while going through the learning process? We will try to answer these questions in the two sections of this chapter. Each of the sections will start with an overview on undirected exploration techniques, then directed strategies will be investigated more thoroughly.

2.1 Exploration in Multi Armed Bandits

2.1.1 Undirected Exploration

The most uninformed and basic way of exploring an unknown environment is to generate actions randomly with uniform probability. This method is often applied if exploration costs do not matter during learning. Sometimes tasks are divided into two phases, namely an exploration and an exploitation phase, and costs are not considered during the exploration phase. This is the case of the *explore-then-commit* algorithm (Algorithm (1.1)) presented in the previous chapter, which explores uniformly the finite number of arms m before starting the exploitation phase, after mK steps. Another common algorithm with undirected uniform exploration is the ϵ -greedy algorithm [72]. One can think of it as an extension of the *explore-then-commit* algorithm which allows to continue exploring with probability ϵ even during the performance phase (i.e., the exploitation phase). The idea is, after a pure exploration phase of mK steps, to exploit the estimated best arm $x_t = \arg \max \hat{\mu}_i(t)$ with probability $(1 - \epsilon_t)$, and explore uniformly the remaining set of arms with probability ϵ_t , at each step. In 2002, Auer et al. [10] analyzed the regret of ϵ -greedy with slowly decreasing ϵ and showed its asymptotic convergence to the optimal solution. These are just asymptotic guarantees, however, and say little about the practical effectiveness of the methods.

Another approach to undirected exploration which is more effective when costs are relevant during learning is *non-uniform* exploration utilizing the current utility estimates to influence action-selection. The higher the expected utility of action i , the more likely i gets selected. This ensures that the learning system explores and exploits simultaneously, as it happens for the ϵ -greedy algorithm, but

in an intuitively more effective way since actions are not chosen uniformly during exploration. An example of utility-driven non-uniform undirected exploration is the Boltzmann-distributed exploration [29]. By defining the average reward of an arm as in Equation (1.3):

$$\hat{\mu}_i(t) = \frac{1}{T_i(t)} \sum_{s=1}^t \mathbb{1}_{\{x_s=i\}} r_s, \quad (2.1)$$

the probability for an action i to get selected is a non-linear function of $\hat{\mu}_i$:

$$Pr(i) = \frac{e^{\hat{\mu}_i \tau^{-1}}}{\sum_{a \in \mathcal{X}} e^{\hat{\mu}_a \tau^{-1}}}. \quad (2.2)$$

Here τ is a gain factor, often called *temperature*, which determines the amount of randomness in the action-selection procedure. With $\tau \rightarrow 0$, pure exploitation is approached, and with $\tau \rightarrow \infty$ the resulting distribution approaches the uniform distribution.

In the rest of this section, we present some techniques of *directed exploration*, which memorize knowledge about the learning process itself and utilize this knowledge to guide the exploration.

2.1.2 Count-based exploration and Upper Confidence Bound

Count-based exploration memorizes knowledge about the number of times $T_i(t)$ action i has been visited up to time-step t , for all $i \in \mathcal{X}$. Strategies based on counting usually evaluate actions by a linear combination of an exploitation term and an exploration term, called the *exploration bonus*, which is a (usually inverse) function of $T_i(t)$. Hence, action x_t is selected in a deterministic fashion as:

$$x_t = \arg \max_{x \in \mathcal{X}} \{\hat{\mu}_x + \text{bonus}(T_x(t-1))\}. \quad (2.3)$$

Such strategy is at the core of the celebrated [Upper Confidence Bound \(UCB\)](#) algorithm [68, 2, 10], that overcomes many of the limitations of strategies based on exploration followed by commitment. The algorithm has many different forms, depending on the distributional assumptions on the noise. Here, we assume the noise is 1-subgaussian, i.e.,:

Definition 2.1.1. Subgaussianity *A random variable X is σ -subgaussian if, for all $\lambda \in \mathbb{R}$, it holds that $\mathbb{E}[\exp(\lambda X)] \leq \exp(\lambda^2 \sigma^2 / 2)$.*

Coupling this property with *Markov's inequality*, we can prove that:

Theorem 2.1.1. [72] *If X is σ -subgaussian, then, for any $\epsilon \geq 0$,*

$$P(X \geq \epsilon) \leq \exp\left(-\frac{\epsilon^2}{2\sigma^2}\right)$$

From this theorem, we can derive a key corollary which gives us precious information about the concentration of the sample mean around the true mean of independent, σ -subgaussian random variables:

Corollary 2.1.1. *Assume that $X_i - \mu$, for $i = 1, 2, \dots, n$ are independent, σ -subgaussian random variables. Then, for any $\epsilon \geq 0$, with probability at least $1 - \delta$, $\delta \in [0, 1]$:*

$$\mu \leq \hat{\mu} + \sqrt{\frac{2\sigma^2 \log(1/\delta)}{n}} \quad \text{and} \quad \mu \geq \hat{\mu} - \sqrt{\frac{2\sigma^2 \log(1/\delta)}{n}},$$

where $\hat{\mu} = \frac{1}{n} \sum_{t=1}^n X_t$.

When considering its options in round t , the learner has observed $T_i(t-1)$ samples from arm i and received rewards from that arm with an empirical mean of $\hat{\mu}_i$. Then an *optimist* candidate for the unknown mean of the i th arm is:

$$UCB_i(t-1, \delta) = \hat{\mu}_i(t-1) + \sqrt{\frac{2 \log(1/\delta)}{T_i(t-1)}}. \quad (2.4)$$

Great care is required when comparing (2.1.1) and (2.4) because in the former the number of samples is the constant n , but in the latter it is a random variable $T_i(t-1)$. Apart from this technicality, the intuition remains that δ is approximately an upper bound on the probability of the event that the above quantity is an underestimate of the true mean. In fact, by Corollary (2.1.1), for any $\delta \in [0, 1]$:

$$Pr\left(\mu \geq \hat{\mu} + \sqrt{\frac{2\sigma^2 \log(1/\delta)}{n}}\right) \leq \delta. \quad (2.5)$$

After having picked all actions once, the **UCB** policy simply picks at each time step t the action i whose $UCB_i(t-1, \delta)$ index is maximum, as shown in Algorithm (2.1).

Algorithm 2.1 UCB(δ) algorithm

```

1: Input:  $K$  arms and  $\delta$ 
2: Choose each action once
3: for  $t = 1, 2, \dots, T$  do
4:   if  $t \leq K$  then
5:      $x_t = t$ 
6:   else
7:      $x_t = \arg \max_i UCB_i(t - 1, \delta)$ 
8:   end if
9: end for

```

The value of $1 - \delta$ is called the *confidence level*, and different choices lead to different algorithms, each with their pros and cons, and sometimes different analysis. For example, Auer et al. [10], present an algorithm originating in [2] called *UCB1* which achieves asymptotic logarithmic regret $\mathcal{O}(\log T)$, for all reward distributions, with no prior knowledge of the reward distribution. Equivalently, we say that UCB1 achieves asymptotic sub-linear pseudo-regret $\tilde{\mathcal{O}}(1)$. *UCB1* takes $\delta = 1/t$, where t is the current time step, resulting in:

$$UCB1_i(t, \delta) = \hat{\mu}_i(t) + \sqrt{\frac{2 \log(t)}{T_i(t)}} \quad (2.6)$$

However, rather than considering 1-subgaussian noise, Auer et al. [10] consider bandits where the payoffs are confined to the $[0, 1]$ interval, which are ensured to be $1/2$ -subgaussian. Better bounds have been proven for modifications of the UCB1 algorithm, for example Improved UCB [12] and Kullback-Leibler Upper confidence Bound (KL-UCB) [46].

2.1.3 Optimism in the Face of Uncertainty

The family of UCB algorithms is of particular relevance because it represents a successful implementation of the principle of *Optimism in the Face of Uncertainty* (OFU), which is applicable to various exploration problems, not only finite-armed stochastic bandits. The OFU principle states that one should choose their actions as if the environment is as nice as plausibly possible.

To illustrate the intuition imagine of being in the same situation depicted in (1.1.1), i.e., a standard lunch break from work. You can choose between your

good old-fashioned favourite restaurant or sampling a restaurant that you never visited before. Taking an optimistic view of the unknown restaurant leads to exploration because without data it *could* be amazing. Then, after trying the new option a few times you can update your statistics about each choice and make a more informed decision. On the other hand, taking a pessimistic view of the new option discourages exploration and you may suffer significant regret if the local options are delicious. The **UCB** strategy assigns to each arm an upper confidence bound that with high probability is an overestimate of the unknown mean reward. The intuitive reason why this leads to sublinear regret is simple. Assuming the upper confidence bound assigned to the optimal arm is indeed an overestimation, then another arm can only be played if its upper confidence bound is larger than that of the optimal arm, which in turn is larger than the mean of the optimal arm. And yet this cannot happen too often because the additional data provided by playing a suboptimal arm means that the upper confidence bound for this arm will eventually fall below that of the optimal arm. The next algorithm that we discuss will be useful to better understand the **OFU** principle and its exploration power, with application to a wider set of arms.

2.1.4 Hierarchical Optimistic Optimization

In 2011, Bubeck et al. [27] proposed a novel optimistic arm selection strategy whose regret improved upon previous results on continuum and Lipschitz bandits (e.g., [64, 62]), extending and generalizing the environment class of application to arbitrary topological spaces. In particular, the setting is that of \mathcal{X} -armed bandits, introduced in (1.1.3). This algorithm is particularly interesting to us for two reasons:

- (i) it applies the **OFU** principle to continuous action spaces, as we wish to do in the context of **RL** Policy Search;
- (ii) it leverages the correlation between arms (expressed as a dissimilarity function) to explore the environment more effectively.

The functioning of the **Hierarchical Optimistic Optimization (HOO)** algorithm is very similar to the **UCB** strategy, with application to a more general set of arms. Consider for example a compact, two-dimensional continuous set of arms, like a square plane in the euclidean space. The strategy is to recursively cutting the square in rectangles, sub-rectangles and so on, building a binary graph of

sets and subsets. We start from the whole square, pull a random arm from it, then divide it in two rectangles. These two rectangles become the new leaves of the graph. Subsequently, we pick one of the two leaves, pull a random arm from it, and spawn two new leaves by sectioning it. Then we repeat the procedure. At each time step, the choice of the leaf (rectangle) depends on an upper bound of the mean payoff of the arms laying within it. All the arms within the same rectangle are considered to have a similar mean payoff because of the structure imposed to the arm set.

Formally, the **HOO** strategy assumes that the decision maker is able to cover the space of arms in a recursive manner, successively refining the regions in the covering such that the diameters of these sets shrink at a known geometric rate when measured with the dissimilarity metric. In particular, the authors define a tree of coverings as:

Definition 2.1.2. (Tree of coverings) *A tree of coverings is a family of measurable subsets $(\mathcal{P}_{(h,i)})_{1 \leq i \leq 2^h, h \geq 0}$ of \mathcal{X} such that for all fixed integer $h \geq 0$, the covering $\bigcup_{1 \leq i \leq 2^h} \mathcal{P}_{h,i} = \mathcal{X}$ holds. Moreover, the elements of the covering are obtained recursively: each subset $\mathcal{P}_{h,i}$ is covered by the two subsets $\mathcal{P}_{h+1,2i-1}$ and $\mathcal{P}_{h+1,2i}$.*

Remark 2.1.1. A typical choice for the coverings in a cubic domain is to let the domains be hyper-rectangles. They can be obtained, for example, in a dyadic manner, by splitting at each step hyper-rectangles in the middle along their longest side, in an axis parallel manner; if all sides are equal, we split them along the first axis.

The number of visits of a node (h, i) up to time-step T is given by the number of visits of every node belonging to $\mathcal{C}(h, i)$, i.e., the set of the node (h, i) and its descendants:

$$T_{h,i}(t) = \sum_{l=1}^t \mathbb{1}_{\{(h_l, i_l) \in \mathcal{C}(h,i)\}}, \quad (2.7)$$

where (h_l, i_l) are the coordinates of the node selected at time step l . Then, the empirical average of the rewards received for the time-points when the path followed by the algorithm has gone through (h, i) is:

$$\hat{\mu}_{h,i}(t) = \frac{1}{T_{h,i}(t)} \sum_{l=1}^t r_l \mathbb{1}_{\{(h_l, i_l) \in \mathcal{C}(h,i)\}}. \quad (2.8)$$

Algorithm 2.2 HOO algorithm

-
- 1: **Input:** the infinite tree of coverings \mathcal{T} , $\rho \in (0, 1)$ and $\nu_1 \in \mathbb{R}_0^+$
 - 2: **Initialize:** $t = 0$, $\mathcal{T}_0 = \emptyset$, $\mathcal{S}_0 = \mathcal{T}$, $B_{h,i}(0) = +\infty \forall (h, i) \in \mathcal{S}_0$
 - 3: Choose the root node $(h_0, i_0) = (0, 1)$ and update $t = t + 1$
 - 4: **for** $t = 1, 2, \dots, T$ **do**
 - 5: Choose a node according to the deterministic rule:

$$(h_t, i_t) = \arg \max_{(h,i) \in \mathcal{S}_t} B_{h,i}(t) \quad (2.11)$$

- 6: Choose, possibly at random, an arm $x_t \in \mathcal{P}_{(h_t, i_t)}$ and collect reward r_t
 - 7: Update $B_{h,i}(t)$ for (h_t, i_t) and all its parent nodes
 - 8: $\mathcal{T}_{t+1} = \mathcal{T}_t \cup (h_t, i_t)$, $\mathcal{S}_{t+1} = \mathcal{S}_t \setminus (h_t, i_t)$
 - 9: **end for**
-

Thus, similarly to the $UCB(\delta)$ algorithm, an upper confidence bound can be defined as:

$$U_{h,i}(t) = \hat{\mu}_{h,i}(t) + \sqrt{\frac{2 \log t}{T_{h,i}(t)}} + \nu_1 \rho^h, \quad (2.9)$$

where $\rho \in (0, 1)$ and $\nu_1 \in \mathbb{R}_0^+$ are parameters of the algorithm. Specifically, given depth h , $\nu_1 \rho^h$ represents an upper bound of the diameter of each node $\mathcal{P}_{(h,i)}$ of the tree of coverings. The existence of such bound is a necessary assumption for the functioning of HOO. Along with the nodes the algorithm stores what the authors call B-values:

$$B_{h,i}(t) = \min\{U_{h,i}(t), \max\{B_{h+1,2i-1}(t), B_{h+1,2i}(t)\}\} \quad (2.10)$$

Finally, let us denote by \mathcal{T} the infinite tree of coverings, by \mathcal{T}_t the set of nodes of the tree that have been picked in previous rounds and by \mathcal{S}_t the nodes which are not in \mathcal{T}_t . Now, for a node (h, i) in \mathcal{S}_t , we define its B-value to be $B_{h,i}(t) = +\infty$. We now have everything we need to present the full HOO strategy in Algorithm (2.2).

The definition and use of B-values, that puts in relationship each node (subset of \mathcal{X}) with all its children (subsets of the subset of \mathcal{X}), shows how the algorithm relies on the correlation between the reward of an arm and that of

its neighbours. Indeed, the proof of the regret achieved by [HOO](#) relies on the following assumption:

Assumption 2.1.1. *The mean-payoff function μ is weakly Lipschitz w.r.t. a dissimilarity metric ℓ , i.e., $\forall x_1, x_2 \in \mathcal{X}$,*

$$\mu^* - \mu(x_2) \leq \mu^* - \mu(x_1) + \max\{\mu^* - \mu(x_1), \ell(x_1, x_2)\}. \quad (2.12)$$

Note that weak Lipschitzness is satisfied whenever μ is 1-Lipschitz, i.e., $\forall x_1, x_2 \in \mathcal{X}$, $|\mu(x_1) - \mu(x_2)| \leq \ell(x_1, x_2)$. On the other hand, weak Lipschitzness implies local (one-sided) 1-Lipschitzness at any maxima. Indeed, at an optimal arm x^* , Equation (2.12) rewrites as $\mu(x^*) - \mu(x_2) \leq \ell(x^*, x_2)$.

By carefully choosing the tree of coverings and the algorithm parameters, the authors show that the regret of the proposed approach is bounded by $\tilde{\mathcal{O}}(\sqrt{T}) = \mathcal{O}(\log \sqrt{T})$. For more details, refer to [27].

2.1.5 Posterior Sampling

Another way to address the exploration-exploitation dilemma in [MABs](#) is by posterior sampling. Particularly relevant is an heuristic called [Thompson Sampling \(TS\)](#), firstly introduced by [122], which has been thoroughly studied in the literature for its good properties. This technique is considered to be close to [UCB](#) algorithms because it also allocates exploratory effort to actions that might be optimal i.e., it also builds upon the [OFU](#) principle [104]. Indeed, similarly to [UCB](#), [TS](#) avoids the under-exploitation of actions that are potentially good and prevents from wasting time on actions that are already known to be bad. The Bayesian approach is what sets [TS](#) apart from the techniques previously mentioned. It requires a prior distribution for each arm as input, which encodes the initial belief that a learner has on each arm reward. Subsequently, at each round t , it samples from each arm distribution, chooses the action with the best reward and updates its posterior distribution by means of the Bayes'rule.

The elements of [TS](#) are the followings:

- (i) a set Θ or parameters θ of the distribution of $r \sim \mathcal{R}_\theta(\cdot|x)$;
- (ii) a prior distribution $P(\theta)$ on these parameters;
- (iii) the history $\mathcal{I}_t = \{x_0, r_0, x_1, r_1, \dots, x_{t-1}, r_{t-1}\}$ of past observations;
- (iv) a likelihood function $P(\mathcal{I}_t|\theta)$;

(v) a posterior distribution $P(\theta|\mathcal{I}_t) \propto P(\mathcal{I}_t|\theta)P(\theta)$.

TS consists in playing the action $x \in \mathcal{X}$ according to the probability that it maximizes the expected reward according to your belief, i.e.,:

$$\arg \max_{x \in \mathcal{X}} \mathbb{E}[r|x] = \arg \max_{x \in \mathcal{X}} \int \mathbb{E}[r|\theta, x] P(\theta|\mathcal{I}_t) d\theta \quad (2.13)$$

Once having observed the reward from the chosen arm, the posterior distribution can be updated using the Bayes' rule. In practice, it is either impossible or computationally expensive to compute the integral above. Therefore, usually we resort to sampling $\hat{\theta}_t \sim P(\theta|\mathcal{I}_t)$ at time t , and then play the arm $x_t = \arg \max_{x \in \mathcal{X}} \mathbb{E}[r|\hat{\theta}_t, x]$. Conceptually, this means that the player instantiates their beliefs randomly in each round, and then acts optimally according to them. In [4] the authors prove that for the K-armed stochastic bandit problem, Thompson Sampling has expected regret of

$$\mathbb{E}[\text{Regret}(T)] \leq (\sqrt{KT \log T}), \quad (2.14)$$

which is identical to the best known problem-independent bound for the expected regret of UCB1 [24].

Example: Thompson Sampling for Bernoulli MAB Suppose that the reward function of each arm i , $i = 1, 2, \dots, K$ is a Bernoulli of parameter p_i : $r_t, i \sim \mathcal{B}(p_i)$ i.e., the result of pulling an arm is either a *success* (with probability p_i) or a *failure* (with probability $1 - p_i$). We know that, given a uniform prior over the parameter $p \sim \mathcal{U}(0, 1) = \text{Beta}(1, 1)$, and having observed $\alpha - 1$ successes and $\beta - 1$ failures, the posterior distribution of the parameter p of a Bernoulli is a Beta distribution of parameters α and β (Beta distributions are frequently adopted as priors because of their conjugacy properties). Hence, **TS** can be performed as shown in Algorithm(2.3).

For a more extensive discussion on algorithms implementing **TS** refer to [105].

2.1.6 Gaussian Process Upper Confidence Bound

We conclude by presenting an algorithm, **Gaussian Process Upper Confidence Bound (GPUCB)** [113], of particular interest to us for three reasons:

Algorithm 2.3 TS for Bernoulli MAB with Beta priors

```

1: Initialize: the prior distribution for each arm as  $Beta(1, 1)$ 
2: for  $t = 1, 2, \dots, T$  do
3:   for  $i = 1, 2, \dots, K$  do
4:     Sample  $\hat{p}_i \sim Beta(\alpha_i, \beta_i)$ 
5:   end for
6:   Pull arm  $x_t = \arg \max_i \hat{p}_i$  and observe  $r_t \in \{0, 1\}$ 
7:   Update distribution:

```

$$(\alpha_i, \beta_i) = \begin{cases} (\alpha_i, \beta_i), & \text{if } x_t \neq i \\ (\alpha_i, \beta_i) + (r_t, 1 - r_t), & \text{if } x_t = i \end{cases} \quad (2.15)$$

```

8: end for

```

- (i) it serves as a further example of application of the **OFU** principle and of **UCB** variant;
- (ii) it formalizes the broad problem of optimizing an unknown, noisy function, that is expensive to evaluate, as a multi-armed bandit problem;
- (iii) it deals with a continuous set of arms.

Indeed, our main contribution builds upon a similar formalization of the **RL** continuous control problem. Moreover, it also represents a case of posterior sampling different from **TS**.

Consider the **MAB** problem presented in Chapter (1), where the reward distribution can be seen as the sum of a reward function (e.g. the expected reward function $\mu(\mathbf{x}_t)$, that here we note as $f(\mathbf{x}_t)$) and noise, i.e., $y_t = \mathcal{R}(\cdot | x_t) = f(\mathbf{x}_t) + \epsilon_t$. As we already know, the goal is to maximize the sum of the rewards collected by choosing a point of the domain $\mathbf{x}_t \in \mathcal{X}$ at each round t up to the horizon T . For example, we might want to find locations of highest temperature in a building by sequentially activating sensors in a spatial network and regressing on their measurements. Each activation draws battery power, so we want to sample from as few sensors as possible. In this context, as in many other **MAB** problems, a natural performance metric is the cumulative regret as defined in Definition (1.1.3). **GPUCB** explicitly encourages additional exploration in a **UCB** sense by choosing, at each step, the arm associated to the highest upper bound of the mean return. Given an arm x this bound is calculated by summing the mean and standard deviation of the estimator of f . In this case, f is sampled from a

Algorithm 2.4 GPUCB

```

1: Input: GP prior  $\mu_0 = 0$ ,  $\mu_0 = 0$ ,  $\beta_t \in \mathbb{R}^+$ 
2: for  $t = 1, 2, \dots, T$  do
3:   Choose  $\mathbf{x}_t = \arg \max_{\mathbf{x} \in \mathcal{X}} \mu_{t-1}(\mathbf{x}) + \sqrt{\beta_t} \sigma_{t-1}(\mathbf{x})$ 
4:   Sample  $y_t = f(\mathbf{x}_t) + \epsilon_t$ 
5:   Perform Bayesian update to obtain  $\mu_t$  and  $\sigma_t$ 
6: end for

```

prior distribution with known mean and standard deviation, whose posterior is updated in a Bayesian fashion at every step. In order to enforce some implicit properties like smoothness without relying on any parametric assumption, the authors of [113] model f as a sample from a **Gaussian Process (GP)**: a collection of dependent random variables, one for each $\mathbf{x} \in \mathcal{X}$, every finite subset of which is multivariate Gaussian distributed [131]. A **GP** is a stochastic process $GP(\mu(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$, specified by its mean $\mu(\mathbf{x}) = \mathbb{E}[f(\mathbf{x})]$ and covariance function $k(\mathbf{x}, \mathbf{x}') = \mathbb{E}(f(\mathbf{x}) - \mu(\mathbf{x}))(f(\mathbf{x}') - \mu(\mathbf{x}'))$. **GPUCB** generally adopts $GP(0, k(\mathbf{x}, \mathbf{x}'))$ as prior distribution over f . A major advantage of working with GPs is the existence of simple analytic formulae for mean and co-variance of the posterior distribution, which allow easy implementation of algorithms. For a noisy sample $\mathbf{y}_T = [y_1, y_2, \dots, y_T]^T$ at points $A_T = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T\}$ over f , the posterior of f is a GP distribution again specified by mean $\mu_T(\mathbf{x})$, covariance $k_T(\mathbf{x}, \mathbf{x}')$ and variance $\sigma_T^2(\mathbf{x})$:

$$\mu_T(\mathbf{x}) = \mathbf{k}_T(\mathbf{x})^T (\mathbf{K}_T + \sigma^2 \mathbf{I})^{-1} \mathbf{y}_T, \quad (2.16)$$

$$k_T(\mathbf{x}, \mathbf{x}') = k(\mathbf{x}, \mathbf{x}') - \mathbf{k}_T(\mathbf{x})^T (\mathbf{K}_T + \sigma^2 \mathbf{I})^{-1} \mathbf{k}_T(\mathbf{x}'), \quad (2.17)$$

$$\sigma_T^2(\mathbf{x}) = k_T(\mathbf{x}, \mathbf{x}), \quad (2.18)$$

$$(2.19)$$

where $\mathbf{k}_T(\mathbf{x}) = [k(\mathbf{x}_1, \mathbf{x}), k(\mathbf{x}_2, \mathbf{x}), \dots, k(\mathbf{x}_T, \mathbf{x})]$ and \mathbf{K}_T is the positive definite kernel matrix $[k(\mathbf{x}, \mathbf{x}')]_{\mathbf{x}, \mathbf{x}' \in A_T}$. The full **GPUCB** procedure, motivated by the **UCB** algorithm, is shown in Algorithm 2.4.

Despite being a successful and easy-to-implement algorithm in many cases, **GPUCB** suffers of two main drawbacks. First, the assumption of f being sampled from a **GP** prior is unrealistic in many cases. Furthermore, finding the upper confidence index in line 3 of Algorithm (2.4) may be hard if the arm set \mathcal{X} is continuous (or generally infinite). Indeed, the bound is multimodal in general.

Although global search heuristics might be effective, no successful practical applications have been registered in the continuous case to our knowledge.

2.2 Exploration in Reinforcement Learning

2.2.1 Undirected Exploration

The most classic undirected exploration strategies in [RL](#) are the same of those introduced earlier for [MABs](#). Indeed, the ϵ -greedy policy is one of the most widely used and known algorithm in reinforcement learning [119]. In the same way, Boltzmann exploration, which uses the exponential of the standard Q-function as the probability of an action, has been extensively studied [123, 29]. Similar policy representations are energy-based models, with the Q-value obtained from an energy model such as a restricted Boltzmann machine [106]. An interesting family of extensions to these techniques goes under the name of *maximum entropy RL*.

Maximum Entropy Reinforcement Learning

As stated in Chapter (1), Equation (1.15), the goal of [RL](#) is to find the optimal policy π^* which maximizes the performance $J(\pi)$. Maximum entropy [RL](#) augments this objective by introducing an entropy term, such that the optimal policy also aims at maximizing its entropy at each visited state:

$$\pi^* = \arg \max_{\pi} \sum_h \mathbb{E}_{s_h, a_h \sim d^{\pi}} [\mathcal{R}(s_h, a_h) + \alpha \mathcal{H}(\pi(\cdot|s_h))], \quad (2.20)$$

where α is a convenient hyperparameter that can be used to determine the relative importance of entropy and reward. This objective function entails a novel approach to undirected exploration w.r.t. Boltzmann exploration. While the latter greedily maximizes entropy at the current time step, maximum entropy [RL](#) explicitly optimizes for policies that aim to reach states where actions will have high entropy in the future. This distinction is crucial, since the maximum entropy objective can be shown to maximize the entropy of the entire trajectory distribution for the policy π , while the greedy Boltzmann exploration approach does not. Optimization problems of this type have been covered in a number of scientific papers, e.g., [59, 135, 50]. In [50], Haarnoja et al. extend the objective presented above to infinite time horizons with the introduction of a discount factor λ :

$$\pi^* = \arg \max_{\pi} \sum_h \mathbb{E}_{s_h, a_h \sim d^{\pi}} \left[\sum_l \gamma^{l-h} \mathbb{E}_{s_l, a_l \sim d^{\pi}} [\mathcal{R}(s_l, a_l) + \alpha \mathcal{H}(\pi(\cdot | s_l)) | s_h, a_h] \right]. \quad (2.21)$$

his objective corresponds to maximizing the discounted expected reward and entropy for future states originating from every state-action tuple (s_h, a_h) weighted by its probability d^{π} under the current policy. Then, they define a soft Q-value Q_{soft}^{π} for any policy π as the expectation under π of the discounted sum of rewards and entropy:

$$Q_{soft}^{\pi} = r_1 + \mathbb{E}_{s_0=s, a_0=a, \tau \sim \pi} \left[\sum_{h=1}^{\infty} \gamma^h (r_{h+1} + \alpha \mathcal{H}(\pi(\cdot | s_h))) \right], \quad (2.22)$$

from which they derive the soft Bellman equation. The authors build upon this novel setting an algorithm called *Soft Q-learning*, which has similar mechanisms to traditional *Q-learning* and adopts deep function approximation to compute the Q-values over a continuous domain. Among the advantages presented over other deep **RL** approaches, Soft Q-learning turns out to be more effective for learning multi-modal policies for exploration. In fact, similarly to **MABs**, during the learning process it is often best to keep trying multiple available options until the agent is confident that one of them is the best. However, deep **RL** algorithms for continuous control typically use unimodal action distributions, which are not well suited to capture such multi-modality. As a consequence, such algorithms may prematurely commit to one mode and converge to suboptimal behaviour, as it happens in the practice. One year later, the same authors of *Soft Q-learning* [50] proposed a powerful extension named *Soft Actor-Critic* [51], which combined off-policy updates with a stable stochastic actor-critic formulation.

Following the same pattern adopted for **MABs**, we proceed now with presenting some techniques that deals with the exploration challenge in a more directed way, i.e., by leveraging on relevant information collected during the learning process to lead exploration more effectively.

2.2.2 Count-based exploration and Intrinsic Motivation

The classic, theoretically-justified **MABs** exploration methods based on counting state-action visitations and turning this count into a bonus reward have been

introduced in (??). Taking inspiration from the MAB literature, many similar count-based algorithms have been designed for tabular RL. It is the case of the notorious E^3 algorithm [61], and two other popular *optimist* algorithms: R_{max} [22] and $UCRL$ [11]. In recent works [17, 121, 91, 34], they have also been adapted to large, non-tabular RL problems. A relevant example is that of Bellamare et al. [17], later developed in [91], which proposes a novel algorithm for deriving a *pseudo-count* from an arbitrary density model. Let ρ be a density model on a finite space \mathcal{X} and $\rho_n(x)$ the probability assigned by the model to x after being trained on a sequence of states $x_1, x_2, \dots, x_n \in \mathcal{X}$. Assume $\rho_n(x) > 0$ for all x, n . The *recording probability* $\rho'_n(x)$ is then the probability the model would assign to x one more time. The *prediction gain* of ρ is:

$$PG_n(x) = \log \rho'_n(x) - \log \rho_n(x). \quad (2.23)$$

Note that $PG_n(x) \geq 0$ for all $x \in \mathcal{X}$ whenever the density model ρ is *learning-positive*, i.e., if $\rho'_n(x) \geq \rho_n(x)$ for all x_1, x_2, \dots, x_n . For learning-positive ρ , the authors define the *pseudo-count* as:

$$\hat{N}_n(x) = \frac{\rho_n(x)(1 - \rho'_n(x))}{\rho'_n(x) - \rho_n(x)}, \quad (2.24)$$

derived from postulating that a single observation of $x \in \mathcal{X}$ should lead to a unit increase in pseudo-count:

$$\rho_n(x) = \frac{\hat{N}_n(x)}{\hat{n}}, \quad \rho'_n(x) = \frac{\hat{N}_n(x) + 1}{\hat{n} + 1}, \quad (2.25)$$

where \hat{n} is the *pseudo-count total*. The pseudo-count generalizes the usual state visitation count function $N_n(x)$. Moreover, under certain assumptions on ρ_n , pseudo-counts grow approximately linearly with real counts. Crucially, the pseudo-count can be approximated using the prediction gain of the density model:

$$\hat{N}_n(x) = (e^{PG_n(x)} - 1)^{-1} \quad (2.26)$$

Its main use is to define an *exploration bonus* that can be added to every extrinsic reward r_n received by the agent. For example, at step n , the agent would face a total reward R_n given by:

$$r'_n = r_n + (\hat{N}_n(x))^{-\frac{1}{2}}, \quad (2.27)$$

which incentivize the agent to try to re-experience surprising situations. In [91] the authors adopt PixelCNN, an advanced neural density model for images first introduced in [84], to supply a pseudo-count. They manage to combine PixelCNN pseudo-counts with different agent architectures to dramatically improve the state of the art on several hard Atari games, a popular set of RL environments for benchmarking.

Interestingly, this notion of pseudo-counts and their application is closely related to the notion of *intrinsic motivation*. In fact, quantities related to prediction gain have been used for similar purposes in the intrinsic motivation literature [73], where they measure an agent's *learning progress* [92]. The concept of *intrinsic motivation* has been introduced in the RL literature by Singh et al. in [33], who borrowed it from psychology. Psychologists call behaviour intrinsically motivated when it is engaged for its own sake rather than as a step toward solving a specific problem of clear practical value. This concept builds on the one of *curiosity*, which has been also extensively investigated in the RL literature after being introduced in it by professor Jürgen Schmidhuber in 1991 [108]. The rationale behind it is that, in some RL scenarios, as well as in human life, rewards are supplied to the agent so sparsely that traditional techniques fails miserably in the learning challenge. This is a problem as the agent receives reinforcement for updating its policy only if it succeeds in reaching a pre-specified goal state. Hoping to stumble into a goal state by chance (i.e. random exploration) is likely to be futile for all but the simplest of environments. Intrinsic motivation / curiosity have been used to instil the need to explore the environment and discover novel states in the agent, regardless of the reward scheme. Most formulations of intrinsic motivation can be grouped into two broad classes:

- (i) encourage the agent to explore *novel* states;
- (ii) encourage the agent to perform actions that reduce the error/uncertainty

in the agent's ability to predict the consequence of its own actions, i.e., its knowledge about the environment.

Measuring *novelty* requires a statistical model of the distribution of the environmental states, as the one described above, whereas measuring prediction error/uncertainty requires building a model of environmental dynamics that predicts the next state s_{h+1} given the current state s_h and the action a_h executed at time h . Evidently, these mechanisms, particularly the first one, are closely related to the concept of count-based exploration. Indeed, Bellamare et al. showed in [17] the close relationship between the two.

Variational Information Maximizing Exploration

To help the reader grasping these concepts, we proceed by describing a successful implementation of the principle of intrinsic motivation, the [Variational Information Maximizing Exploration \(VIME\)](#) algorithm [53]. VIME makes use of the information gain about the agent's internal belief of the dynamics model as a driving force, as described in the following. The approach taken is model-based, where the agent models the environment dynamics via a model $p(s_{h+1}|s_h, a_h, \theta)$, parametrized by the random variable Θ with values $\theta \in \Theta$. Assuming a prior $p(\theta)$, it keeps a distribution over dynamic models through a distribution over θ , which is updated in a Bayesian fashion. The authors formalize the intrinsic goal of taking actions that maximize the reduction in uncertainty about the dynamics as taking actions that lead to states that are maximally informative about the dynamics model. In other terms, the agent is encouraged to maximize the mutual information between the next state distribution S_{h+1} and the model parameter Θ :

$$I(S_{h+1}; \Theta | \xi_h, a_h) = \mathbb{E}_{s_{h+1} \sim \mathcal{P}(\cdot | \xi_h, a_h)} [D_{KL}[p(\theta | \xi_h, a_h, s_{h+1}) || p(\theta | \xi_h)]] , \quad (2.28)$$

where $D_{KL}(P||Q)$ is the [Kullback-Leibler \(KL\)](#) divergence between probabilities P and Q , \mathcal{P} are the true environment dynamics and $\xi_h = \{s_1, a_1, \dots, s_h\}$ is the history of the agent up until time step t . This KL divergence can be interpreted as information gain. Therefore we can add each term $I(S_{h+1}; \Theta | \xi_h, a_h)$ as an *intrinsic reward* to the standard reward r_h obtained by the agent at time step t . The trade-off between exploitation and exploration can now be realized explicitly as follows:

$$r'_h = r_h + \eta D_{KL}[p(\theta|\xi_h, a_h, s_{h+1})||p(\theta|\xi_h)], \quad (2.29)$$

with $\eta \in \mathbb{R}^+$ being a hyperparameter controlling the urge to explore. The biggest practical issue with maximizing information gain for exploration is that the computation of this equation requires calculating the posterior $p(\theta|\xi_h, a_h, s_{h+1})$, which is generally intractable. The practical solution adopted by the authors for calculating the posterior $p(\theta|\mathcal{D})$ for a dataset \mathcal{D} is to approximate it through an alternative distribution $q(\theta; \phi)$, parametrized by ϕ , by minimizing $D_{KL}[q(\theta; \phi)||p(\theta|\mathcal{D})]$. This is done through maximization of the *variational lower bound* $L[q(\theta; \phi), \mathcal{D}]$, also called *evidence lower bound* [19]:

$$L[q(\theta; \phi), \mathcal{D}] = \mathbb{E}_{\theta \sim q(\cdot|\phi)} [\log p(\mathcal{D}|\theta)] - D_{KL}[q(\theta; \phi)||p(\theta)]. \quad (2.30)$$

Rather than computing information gain in Equation (2.29) explicitly, we compute an approximation to it, leading to the following total reward:

$$r'_h = r_h + \eta D_{KL}[q(\theta; \phi_{h+1})||q(\theta; \phi_h)], \quad (2.31)$$

with ϕ_{h+1} the updated and ϕ_t the old parameters representing the agent's belief. Natural candidates for parametrizing the agent's dynamics model $q(\theta; \phi)$ are Bayesian neural networks, whose weight distribution ($q(\theta; \phi)$ itself) is given by the fully factorized Gaussian distribution [20]. This is particularly convenient as it allows for a simple analytical formulation of the KL divergence, that can be easily approximated. In fact, [VIME](#) approximates the KL divergence between the former belief ϕ_t on the dynamics and the approximate updated belief ϕ'_t . Algorithm 2.5 outline the procedure. For more details about the implementation the reader should refer to [53].

2.2.3 Posterior Sampling

The [TS](#) technique described in the previous section has been adopted and investigated in the framework of [RL](#) as well [116, 87, 88, 86]. Here, [TS](#) involves sampling a statistically plausible set of action values (or policies) and selecting the maximizing action (or best policy). These values can be generated, for

Algorithm 2.5 [VIME](#)

```

1: for each epoch  $t$  do
2:   for  $h = 1, 2, \dots, H$  do
3:     Generate action  $a_h \sim \pi(s_h)$  and sample  $s_{h+1} \sim \mathcal{P}(\cdot | \xi_h, a_h)$ , get  $r_h$ 
4:     Add triplet  $(s_h, a_h, s_{h+1})$  to FIFO replay pool  $R$ 
5:     Compute the approximated divergence  $D_{KL}[q(\theta; \phi'_t) || q(\theta; \phi_t)]$ 
6:     Construct  $r'_h = r_h + \eta D_{KL}[q(\theta; \phi'_t) || q(\theta; \phi_t)]$ 
7:   end for
8:   Sample randomly  $\mathcal{D}$  from  $R$ 
9:   Minimize  $-L[q(\theta; \phi_t), \mathcal{D}]$  and obtain the updated posterior  $q(\theta; \phi_{t+1})$ 
10:  Use rewards  $r'_1, r'_2, \dots, r'_H$ , to update policy  $\pi$  using any standard RL
    method
11: end for

```

example, by sampling from the posterior distribution over MDPs and computing the state-action value function of the sampled MDP. This approach, originally proposed in [116], is called posterior sampling for reinforcement learning. In [89], the authors present theoretical and experimental arguments to show that posterior sampling is better than optimism in synthesizing efficient exploration with powerful generalization. Although we build our work leveraging on the principle of optimism in the face of uncertainty, posterior sampling appears to be an interesting option to further investigate. Indeed, as we will see, the formalization of the [RL](#) problem that we propose in this paper seems to be a good testing ground for [TS](#).

Chapter 3

Optimistic Policy Optimization via Multiple Importance Sampling

In this chapter we present the main theoretical contributions of this thesis project. In Section (3.1), we extend Section (1.5) to develop robust MIS estimators that will play an essential role in the algorithms proposed. In Section (3.2) we provide a formalization of the online policy optimization problem. The algorithms are presented in Section (3.3) and analyzed in Section (3.4). The proposed algorithms, called Optimistic Policy opTimization via Multiple Importance Sampling with Truncation (OPTIMIST) and OPTIMIST2, are based on the OFU principle and follows the UCB strategy, both introduced in Section (1.1) and covered with practical implementations in (2.1). The idea is to leverage these techniques to deal with the problem of exploration in continuous-action RL, whose solutions proposed so far have been largely heuristic, as we have seen in Chapter (2). However, the solutions proposed here should not be interpreted as an application of the MAB framework to PS but rather as a way to formulate exploration in policy search as a MAB-like problem

3.1 Robust Importance Sampling Estimation

In this section, we discuss how to perform a robust importance weighting estimation. Recently it has been observed that, in many cases of interest, the plain estimator (1.37) presents problematic tail behaviors [80], preventing the use of

exponential concentration inequalities. In fact, unless we require that $d_\infty(P\|\Phi)$ is finite, i.e., that the importance weight have finite supremum, there always exists a value $\alpha > 1$ such that $d_\alpha(P\|\Phi) = +\infty$. A common heuristic to address this problem consists in truncating the weight [54]:

$$\check{\mu}_{\text{IS}} = \frac{1}{N} \sum_{i=1}^N \min \{M, w_{P/Q}(z_i)\} f(z_i), \quad (3.1)$$

where M is a threshold to limit the magnitude of the importance weight. Similarly, for the multiple importance sampling case, restricting to the BH, we have:

$$\check{\mu}_{\text{BH}} = \frac{1}{N} \sum_{k=1}^K \sum_{i=1}^{N_k} \min \left\{ M, \frac{p(z_{ik})}{\sum_{j=1}^K \frac{N_j}{N} q_j(z_{ik})} \right\} f(z_{ik}). \quad (3.2)$$

Clearly, since we are changing the importance weights, we introduce a bias term, but, by reducing the range of the estimation, we get a benefit in terms of variance. Below, we present the bias-variance analysis of the estimator $\check{\mu}_{\text{BH}}$ and we conclude by showing that we are able, using an adaptive truncation, to guarantee an exponential concentration (differently from the non-truncated case).

Lemma 3.1.1. *Let P and $\{Q_k\}_{k=1}^N$ be probability measures on the measurable space $(\mathcal{Z}, \mathcal{F})$ such that $P \ll Q_k$ and there exists $\epsilon \in (0, 1]$ s.t. $d_{1+\epsilon}(P\|Q_k) < \infty$ for $k = 1, \dots, K$. Let $f : \mathcal{Z} \rightarrow \mathbb{R}_+$ be a bounded non-negative function, i.e., $\|f\|_\infty < \infty$. Let $\check{\mu}_{\text{BH}}$ be the truncated balance heuristic estimator of f , as defined in (3.2), using N_k i.i.d. samples from each Q_k . Then, the bias of $\check{\mu}_{\text{BH}}$ can be bounded as:*

$$0 \leq \mu - \mathbb{E}_{z_{ik} \sim Q_k} [\check{\mu}_{\text{BH}}] \leq \|f\|_\infty M^{-\epsilon} d_{1+\epsilon}(P\|\Phi)^\epsilon, \quad (3.3)$$

and the variance of $\check{\mu}_{\text{BH}}$ can be bounded as:

$$\mathbb{V}\text{ar}_{z_{ik} \sim Q_k} [\check{\mu}_{\text{BH}}] \leq \|f\|_\infty^2 M^{1-\epsilon} \frac{d_{1+\epsilon}(P\|\Phi)^\epsilon}{N}, \quad (3.4)$$

where $N = \sum_{k=1}^K N_k$ is the total number of samples and $\Phi = \sum_{k=1}^K \frac{N_k}{N} Q_k$ is a finite mixture.

It is worth noting that, by selecting $\epsilon = 1$, equation (3.4) reduces to Lemma 1.5.1, as the truncation operation can only reduce the variance. Clearly, the smaller we choose M , the larger the bias. Overall, we are interested in mining the joint contribution of bias and variance. Keeping P and Φ fixed we observe that the bias depends only on M , whereas the variance depends on M and on

the number of samples N . Intuitively, we can allow larger truncation thresholds M as the number of samples N increases. The following result states that, when using an *adaptive threshold* depending on N , we are able to reach exponential concentration.

Theorem 3.1.1. *Let P and $\{Q_k\}_{k=1}^N$ be probability measures on the measurable space $(\mathcal{Z}, \mathcal{F})$ such that $P \ll Q_k$ and there exists $\epsilon \in (0, 1]$ s.t. $d_{1+\epsilon}(P \| Q_k) < \infty$ for $k = 1, \dots, K$. Let $f : \mathcal{Z} \rightarrow \mathbb{R}_+$ be a bounded non-negative function, i.e., $\|f\|_\infty < \infty$. Let $\check{\mu}_{BH}$ be the truncated balance heuristic estimator of f , as defined in (3.2), using N_k i.i.d. samples from each Q_k . Let $M_N = \left(\frac{Nd_{1+\epsilon}(P \| \Phi)^\epsilon}{\log \frac{1}{\delta}} \right)^{\frac{1}{1+\epsilon}}$, then with probability at least $1 - \delta$:*

$$\check{\mu}_{BH} \leq \mu + \|f\|_\infty \left(\sqrt{2} + \frac{1}{3} \right) \left(\frac{d_{1+\epsilon}(P \| \Phi) \log \frac{1}{\delta}}{N} \right)^{\frac{\epsilon}{1+\epsilon}}, \quad (3.5)$$

and also, with probability at least $1 - \delta$:

$$\check{\mu}_{BH} \geq \mu - \|f\|_\infty \left(\sqrt{2} + \frac{4}{3} \right) \left(\frac{d_{1+\epsilon}(P \| \Phi) \log \frac{1}{\delta}}{N} \right)^{\frac{\epsilon}{1+\epsilon}}. \quad (3.6)$$

Our adaptive truncation approach and the consequent concentration results resemble the ones proposed in [25]. However, unlike [25] we do not remove samples with too high value, but we exploit the nature of the importance weighted estimator only to limit the weight magnitude. Indeed, this form of truncation turned out to be very effective in practice [54].

3.2 Problem Formalization

The online learning problem that we aim to solve does *not* fall within the traditional **MAB** framework (not in its basic version, anyway) and can benefit from an ad-hoc formalization, provided in this section.

Let $\mathcal{X} \subseteq \mathbb{R}^d$ be our decision set, or *arm set* in **MAB** jargon. Let (Ω, \mathcal{F}, P) be a probability space. Let $\{Z_{\mathbf{x}} : \Omega \rightarrow \mathcal{Z} \mid \mathbf{x} \in \mathcal{X}\}$ be a set of continuous random vectors parametrized by \mathcal{X} , with common sample space $\mathcal{Z} \subseteq \mathbb{R}^m$. We denote with $p_{\mathbf{x}}$ the probability density function of $Z_{\mathbf{x}}$. Finally, let $f : \mathcal{Z} \rightarrow \mathbb{R}$ be a bounded *payoff function*, and $\mu(\mathbf{x}) = \mathbb{E}_{z \sim p_{\mathbf{x}}} [f(z)]$ its expectation under $p_{\mathbf{x}}$. For each iteration $t = 0, \dots, T$, we select an arm \mathbf{x}_t , draw a sample z_t from $p_{\mathbf{x}_t}$, and observe payoff $f(z_t)$, up to horizon T . The goal is to maximize the expected

total payoff:

$$\max_{\mathbf{x}_0, \dots, \mathbf{x}_T \in \mathcal{X}} \sum_{t=0}^T \mathbb{E}_{z_t \sim p_{\mathbf{x}_t}} [f(z_t)] = \max_{\mathbf{x}_0, \dots, \mathbf{x}_T \in \mathcal{X}} \sum_{t=0}^T \mu(\mathbf{x}_t). \quad (3.7)$$

Although we can evaluate $p_{\mathbf{x}}$ for each $\mathbf{x} \in \mathcal{X}$, we can only observe $f(z_t)$ for the z_t that are actually sampled. This models precisely the online, episodic policy optimization problem. Within this problem formulation, we distinguish between two categories of policy optimization: *action-based* and *parameter-based* policy optimization.

- In *action-based* policy optimization, \mathcal{X} corresponds to the parameter space Θ of a class of stochastic policies $\{\pi_{\boldsymbol{\theta}} \mid \boldsymbol{\theta} \in \Theta\}$, \mathcal{Z} to the set of possible trajectories, $p_{\mathbf{x}}$ to the density $p_{\boldsymbol{\theta}}$ over trajectories induced by policy $\pi_{\boldsymbol{\theta}}$, and $f(z)$ to cumulated reward $\mathcal{R}(\tau)$.
- In *parameter-based* policy optimization, \mathcal{X} corresponds to the hyperparameter space Ξ of a class of stochastic hyperpolicies $\{\nu_{\boldsymbol{\xi}} \mid \boldsymbol{\xi} \in \Xi\}$, \mathcal{Z} to the policy parameter space Θ , $p_{\mathbf{x}}$ to hyperpolicy $\nu_{\boldsymbol{\xi}}$, and $f(z)$ to performance $J(\boldsymbol{\theta})$.

In both cases, each iteration corresponds to a single episode, and horizon T is the total number of episodes (not to be confused with the trajectory horizon H). With reference to the standard PS framework, the first category is closely related to standard PG methods that perform a search in a parametric policy space by following the gradient of the utility function. The second, is more related to methods searching directly in the space of parameters like PGPE. From now on, we will refer to (3.7) simply as the policy optimization problem.

Remark 3.2.1. In abstract terms, (3.7) is a sequential decision problem over a functional space of random variables, and may have applications beyond policy optimization.

The peculiarity of this framework, compared to the classic MAB one, is the special structure existing over the arms. In particular, the expected payoff μ of different arms is correlated thanks to the stochasticity of the $p_{\mathbf{x}}$'s on a common sample space \mathcal{Z} . We *could*, of course, frame policy optimization as a MAB problem, at the cost of ignoring some structure. It would be enough to regard $\mu(\mathbf{x})$ as the expectation of a totally unknown, stochastic reward function. This would put us in the continuous MAB framework [63], but would ignore

the special arm correlation. In the following, we will show how this correlation can be exploited to guarantee efficient exploration. This insight stems from the literature on \mathcal{X} -armed bandits, as discussed in (1.1.3) and (2.1.4).

3.3 Algorithms

In this section, we use the mathematical tools presented so far to design a policy search algorithm that efficiently explores the space of solutions. The proposed algorithm, called **OPTIMIST**, is based on the **OFU** principle and follows the **UCB** strategy.

To apply the **UCB** strategy to the policy optimization problem described above, we need an estimate of the objective $\mu(\mathbf{x})$ and a confidence region. We use importance sampling to capture the correlation among the arms. In particular, to better use all the data that we collect, we would like to use a multiple importance sampling estimator like the one from (1.38). Unfortunately, the heavy-tailed behavior of this estimator would result in an inefficient exploration. Instead, we use the robust balance heuristic estimator $\check{\mu}_{\text{BH}}$ from (3.2), which has better tail behavior. To simplify the notation, we treat each sample \mathbf{x} as a distinct one. This is w.l.o.g. (as each sample is always multiplied by its number of occurrences anyway) and corresponds to the case $K = t - 1$ and $N_k \equiv 1$. Hence, at each iteration t :

$$\check{\mu}_t(\mathbf{x}) = \sum_{k=0}^{t-1} \min \left\{ M_{t-1}, \frac{p_{\mathbf{x}}(z_k)}{\sum_{j=1}^{t-1} p_{\mathbf{x}_j}(z_k)} \right\} f(z_k), \quad (3.8)$$

where $M_t = \left(\frac{td_{1+\epsilon}(p_{\mathbf{x}}\|\Phi_t)^\epsilon}{\log \frac{1}{\delta_t}} \right)^{\frac{1}{1+\epsilon}}$ and $\Phi_t = \frac{1}{t} \sum_{k=0}^{t-1} p_{\mathbf{x}_k}$. According to Theorem (3.1.1), the following *index*:

$$\begin{aligned} B_t^\epsilon(\mathbf{x}, \delta_t) &:= \check{\mu}_t(\mathbf{x}) \\ &+ \|f\|_\infty \left(\sqrt{2} + \frac{4}{3} \right) \left(\frac{d_{1+\epsilon}(p_{\mathbf{x}_t}\|\Phi_t) \log \frac{1}{\delta_t}}{t} \right)^{\frac{\epsilon}{1+\epsilon}}, \end{aligned} \quad (3.9)$$

is an upper bound on $\mu(\mathbf{x})$ with probability at least $1 - \delta_t$, i.e., an upper confidence bound. The **OPTIMIST** algorithm simply selects, at each iteration t , the arm with the largest value of the index $B_t^\epsilon(\mathbf{x})$, breaking ties deterministically. The pseudocode is provided in Algorithm (3.1). The initial arm \mathbf{x}_0 is arbitrary, as no prior information is available. The regret analysis of Section (3.4) will provide

Algorithm 3.1 OPTIMIST

-
- 1: **Input:** initial arm \mathbf{x}_0 , confidence schedule $(\delta_t)_{t=1}^T$, order $\epsilon \in (0, 1]$
 - 2: Draw sample $z_0 \sim p_{\mathbf{x}_0}$ and observe payoff $f(z_0)$
 - 3: **for** $t = 1, \dots, T$ **do**
 - 4: Select arm $\mathbf{x}_t = \arg \max_{\mathbf{x} \in \mathcal{X}} B_t^\epsilon(\mathbf{x}, \delta_t)$
 - 5: Draw sample $z_t \sim p_{\mathbf{x}_t}$ and observe payoff $f(z_t)$
 - 6: **end for**
-

a confidence schedule $(\delta_t)_{t=1}^T$. Knowledge of the actual horizon T is not needed. Although we can use any $\epsilon \in (0, 1]$, we suggest to use $\epsilon = 1$ in practice, as it yields the more common 2-Rényi divergence. To be able to compute the indexes (or to perform any kind of index maximization), the algorithm needs to store all the \mathbf{x}_t together with the observed pay-offs $f(z_t)$, hence $\mathcal{O}(Td)$ space is required, where d is the dimensionality of the arm space \mathcal{X} (not to be confused with cardinality $|\mathcal{X}|$, which may be infinite).

The optimization step (line 4) may be very difficult when \mathcal{X} is not discrete [113], as the index $B_t^\epsilon(\mathbf{x}, \delta_t)$ is non-convex and non-differentiable. Global optimization methods could be applied at the cost of giving up theoretical guarantees. In practice, this direction may be beneficial, but we leave it to future, more application-oriented work. Instead, we propose a general discretization method. The key intuition, common in the continuous MAB literature, is to make the discretization progressively finer. The pseudocode for this variant, called OPTIMIST2, is reported in Algorithm (3.2). Note that the arm space \mathcal{X} itself is fixed (and infinite), as adaptive discretization is performed for optimization purposes only. Implementing any variant of OPTIMIST to solve a policy optimization problem, whether in the action-based or in the parameter-based formulation, requires some additional caveats, discussed in Section (4.1).

3.4 Regret Analysis

In this section, we provide high-probability guarantees on the quality of the solution provided by Algorithm (3.1). First, we rephrase the optimization problem (3.1) in terms of *regret minimization*. The instantaneous regret, as defined in (1.1.2), is:

$$\Delta_t = \mu(\mathbf{x}^*) - \mu(\mathbf{x}_t), \quad (3.10)$$

where $\mathbf{x}^* = \arg \max_{\mathbf{x} \in \mathcal{X}} \mu(\mathbf{x})$. Let $\text{Regret}(T) = \sum_{t=0}^T \Delta_t$ be the total regret, as in (1.1.3). As $\mu(\mathbf{x}^*)$ is a constant, problem (3.7) is trivially equivalent to:

$$\min_{\mathbf{x}_0, \dots, \mathbf{x}_T \in \mathcal{X}} \text{Regret}(T). \quad (3.11)$$

In the following, we will show that Algorithm (3.1) yields sublinear regret under some mild assumptions. The proofs combine techniques from [113] and [25] and are reported in Appendix (A). First, we need the following assumption on the Rényi divergence:

Assumption 3.4.1. *For all $t = 1, \dots, T$, the $(1 + \epsilon)$ -Rényi divergence is uniformly bounded as:*

$$\sup_{\mathbf{x}_0, \mathbf{x}_1, \dots, \mathbf{x}_t \in \mathcal{X}} d_{1+\epsilon}(p_{\mathbf{x}_t} \| \Phi_t) = v_\epsilon < \infty,$$

where $\Phi_t = \frac{1}{t} \sum_{k=0}^{t-1} p_{\mathbf{x}_k}$,

which can be easily enforced through careful policy (or hyperpolicy) design, as discussed in 4.1.2.

3.4.1 Discrete arm set

We start from the discrete case, where $|\mathcal{X}| = K \in \mathbb{N}_+$. This setting is particularly convenient, as the optimization step can be trivially solved in time $\mathcal{O}(Kt)$ per iteration,¹ where t is from evaluation of (3.8) via clever caching. This sums up to total time $\mathcal{O}(KT^2)$. It is also of practical interest: even in applications where \mathcal{X} is naturally continuous (e.g., robotics), the set of solutions that can be actually tried in practice may sometimes be constrained to a discrete, reasonably small set. In this simple setting, **OPTIMIST** achieves $\tilde{\mathcal{O}}(T^{\frac{1}{1+\epsilon}})$ regret:

Theorem 3.4.1. *Let \mathcal{X} be a discrete arm set with $|\mathcal{X}| = K \in \mathbb{N}_+$. Under Assumption (3.4.1), Algorithm (3.1) with confidence schedule $\delta_t = \frac{3\delta}{t^2 \pi^2 K}$ guarantees, with probability at least $1 - \delta$:*

$$\begin{aligned} \text{Regret}(T) &\leq \Delta_0 \\ &+ CT^{\frac{1}{1+\epsilon}} \left[v_\epsilon \left(2 \log T + \log \frac{\pi^2 K}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}}, \end{aligned}$$

where $C = (1 + \epsilon) (2\sqrt{2} + \frac{5}{3}) \|f\|_\infty$, and Δ_0 is the instantaneous regret of the initial arm \mathbf{x}_0 .

¹We consider the evaluation of pdf's, payoffs and Rényi divergences in (3.8) atomic, as it is heavily problem-dependent.

This yields a $\tilde{\mathcal{O}}(\sqrt{T})$ regret when $\epsilon = 1$.

3.4.2 Compact arm set

Now, we consider the more general case of a compact arm set $\mathcal{X} \in \mathbb{R}^d$. This case is also more interesting as it allows to tackle virtually any RL task. We can assume, w.l.o.g., that \mathcal{X} is entirely contained in a box $[-D, D]^d$, with $D \in \mathbb{R}_+$. We also need the following assumption on the expected payoff:

Assumption 3.4.2. *The expected payoff μ is Lipschitz continuous, i.e., there exists a constant $L > 0$ such that, for every $\mathbf{x}, \mathbf{x}' \in \mathcal{X}$:*

$$|\mu(\mathbf{x}') - \mu(\mathbf{x})| \leq L \|\mathbf{x} - \mathbf{x}'\|_1.$$

This assumption is easily satisfied for policy optimization, as shown in the following:

Lemma 3.4.1. *In the policy optimization problem, Assumption 3.4.2 can be replaced by:*

$$\sup_{s \in \mathcal{S}, \theta \in \Theta} \mathbb{E}_{a \sim \pi_\theta} [|\nabla_\theta \log \pi_\theta(a|s)|] \leq \mathbf{u}_1, \quad (3.12)$$

in the action-based paradigm, and by:

$$\sup_{\xi \in \Xi} \mathbb{E}_{\theta \sim \rho_\xi} [|\nabla_\xi \log \rho_\xi(\theta)|] \leq \mathbf{u}_2, \quad (3.13)$$

in the parameter-based paradigm, where \mathbf{u}_1 and \mathbf{u}_2 are d -dimensional vectors and the inequalities are component-wise.

In the proof (Appendix (A)), we show how to derive the corresponding Lipschitz constants, and show how (3.12) and (3.13) are satisfied by the commonly-used Gaussian policy and hyperpolicy, respectively. This is enough for **OPTIMIST** to achieve $\tilde{\mathcal{O}}(d^{\frac{\epsilon}{1+\epsilon}} T^{\frac{1}{1+\epsilon}})$ regret:

Theorem 3.4.2. *Let \mathcal{X} be a d -dimensional compact arm set with $\mathcal{X} \subseteq [-D, D]^d$. Under Assumptions (3.4.1) and (3.4.2), Algorithm (3.1) with confidence schedule $\delta_t = \frac{6\delta}{\pi^2 t^2 (1+d^d t^{2d})}$ guarantees, with probability at least $1 - \delta$:*

$$\begin{aligned} \text{Regret}(T) &\leq \Delta_0 \\ &+ CT^{\frac{1}{1+\epsilon}} \left[v_\epsilon \left(2(d+1) \log T + d \log d + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} \\ &+ \frac{\pi^2 LD}{6}, \end{aligned}$$

Algorithm 3.2 OPTIMIST2

-
- 1: **Input:** initial arm \mathbf{x}_0 , confidence schedule $(\delta_t)_{t=1}^T$, discretization schedule $(\tau_t)_{t=1}^T$, order $\epsilon \in (0, 1]$
 - 2: Draw sample $z_0 \sim p_{\mathbf{x}_0}$ and observe payoff $f(z_0)$
 - 3: **for** $t = 1, \dots, T$ **do**
 - 4: Discretize \mathcal{X} with a uniform grid $\tilde{\mathcal{X}}_t$ of τ_t^d points
 - 5: Select arm $\mathbf{x}_t = \arg \max_{\mathbf{x} \in \tilde{\mathcal{X}}_t} B_t^\epsilon(\mathbf{x}, \delta_t)$
 - 6: Draw sample $z_t \sim p_{\mathbf{x}_t}$ and observe payoff $f(z_t)$
 - 7: **end for**
-

where $C = (1 + \epsilon) (2\sqrt{2} + \frac{5}{3}) \|f\|_\infty$, and Δ_0 is the instantaneous regret of the initial arm \mathbf{x}_0 .

This yields a $\tilde{O}(\sqrt{dT})$ regret when $\epsilon = 1$. Unfortunately, the optimization step may be very time-consuming. In some applications, we can assume the time required to draw samples to dominate the computational time. In fact, drawing a sample (Algorithm (3.1), line 2) corresponds to generating a whole trajectory of experience, which may take a long time, especially in real-world applications.

3.4.3 Discretization

When optimization over the infinite arm space \mathcal{X} is not feasible, Algorithm (3.2) can be used instead. This variant restricts the optimization to a progressively finer grid $\tilde{\mathcal{X}}_t$ of $(\tau_t)^d$ vertices. A reasonably coarse discretization schedule can be used at the price of a worse (but still sublinear) regret:

Theorem 3.4.3. *Let \mathcal{X} be a d -dimensional compact arm set with $\mathcal{X} \subseteq [-D, D]^d$. For any $\kappa \geq 2$, under Assumptions (3.4.1) and (3.4.2), Algorithm (3.2) with confidence schedule $\delta_t = \frac{6\delta}{\pi^2 t^2 (1 + \lceil t^{1/\kappa} \rceil^d)}$ and discretization schedule $\tau_t = \lceil t^{1/\kappa} \rceil$ guarantees, with probability at least $1 - \delta$:*

$$\text{Regret}(T) \leq \Delta_0 + C_1 T^{(1-\frac{1}{\kappa})} d + C_2 T^{\frac{1}{1+\epsilon}} \cdot \left[v_\epsilon \left((2 + d/\kappa) \log T + d \log 2 + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}},$$

where $C_1 = \frac{\kappa}{\kappa-1} LD$, $C_2 = (1 + \epsilon) (2\sqrt{2} + \frac{5}{3}) \|f\|_\infty$, and Δ_0 is the instantaneous regret of the initial arm \mathbf{x}_0 .

Let us focus on the case $\epsilon = 1$, which is the only one of practical interest in the scope of this paper. For $\kappa = 2$, we obtain regret $\tilde{O}(d\sqrt{T})$. Unfortunately,

the time required for optimization is exponential in arm space dimensionality d , i.e., $\mathcal{O}(\lceil t^{\frac{1}{\kappa}} \rceil^d)$. For $d \geq 2$, we can break the curse of dimensionality by taking $\kappa = d$. In this case, the regret is $\tilde{\mathcal{O}}\left(dT^{(1-\frac{1}{d})}\right)$. On the other hand, the time per iteration is only $\mathcal{O}(t^2)$. Note that the regret is sublinear for any choice of κ . Going further: for any $\zeta > 0$, $\kappa = \frac{d}{\zeta}$ grants $\mathcal{O}(t^{1+\zeta})$ time per iteration at the cost of $\tilde{\mathcal{O}}\left(dT^{(1-\frac{\zeta}{d})}\right)$ regret.

Remark 3.4.1. The worse dependency $\tilde{\mathcal{O}}(d)$ of the regret on the arm space dimensionality (w.r.t. $\tilde{\mathcal{O}}(\sqrt{d})$ of Algorithm (3.1)) is also necessary to prevent the time per iteration from being exponential in d .

Chapter 4

Numerical Simulations

In this chapter, we start by discussing two practical aspects related to the experimental applications of the algorithms described in Chapter (3). Then, we proceed by showing the results of our numerical simulations on three RL benchmarking challenges: the [Linear Quadratic Gaussian regulation \(LQG\)](#), the continuous mountain car problem and the inverted pendulum.

The programming language chosen for implementing all the numerical simulations discussed in this chapter is Python. The code is publicly available on GitHub¹, and it is built upon the OpenAI Baselines library².

4.1 Practical Aspects

In the numerical simulations that will be presented in the following sections we place ourselves in the *parameter-based* [PS](#) setting (see Section (3.2) for details). We adopt Gaussian distributions as target and behavioural hyperpolicies $\nu_{\xi} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, from which the policy parameters $\boldsymbol{\theta}$ are drawn. In particular, we will adopt diagonal hyperpolicies ν_{ξ} , with hyperparameters $\boldsymbol{\xi} = \{\boldsymbol{\theta}, \boldsymbol{\Sigma}\}$, of the form:

¹<https://github.com/T3p/baselines/tree/exploration/baselines>

²<https://github.com/openai/baselines>

$$\nu_{\xi}(\boldsymbol{\theta}) = \frac{1}{\sqrt{(2\pi)^m |\boldsymbol{\Sigma}|}} \exp \left(-\frac{1}{2} (\boldsymbol{\theta} - \boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{\theta} - \boldsymbol{\mu}) \right) \quad (4.1)$$

$$= \frac{1}{\sqrt{(2\pi)^m \prod_{i=1}^m \sigma_i^2}} \exp \left(-\frac{1}{2} \sum_{i=1}^m \frac{(\theta_i - \mu_i)^2}{\sigma_i^2} \right). \quad (4.2)$$

This allows the use of a deterministic controller $\pi_{\boldsymbol{\theta}} : \boldsymbol{\theta} \in \Theta \subseteq \mathbb{R}^m$ for sampling the trajectories, that we define as $\pi_{\boldsymbol{\theta}}(a|s) = \delta(a - \boldsymbol{\theta}s)$. This parameter-based setting follows the one adopted in [PGPE](#), as described in [\(1.4.4\)](#).

This distribution choice for our target and behavioural hyperpolicies allows a comfortable computation of the robust balance heuristic estimator $\check{\mu}_t(\mathbf{x})$ defined in Equation [\(3.8\)](#). Unfortunately, that is not all for the computation of the upper bound $B_t^e(\mathbf{x}, \delta_t)$, that we need to optimize in each iteration t of the [OPTIMIST](#) algorithm [\(3.9\)](#).

4.1.1 Divergence Between Gaussian Multivariate Distributions

Indeed, [OPTIMIST](#) requires also to compute the exponentiated Rényi divergence between the currently considered distribution $p_{\mathbf{x}}$ and the mixture Φ_t , i.e., $d_{1+\epsilon}(p_{\mathbf{x}} \parallel \Phi_t) = d_{1+\epsilon}(\nu_{\xi} \parallel \Phi_t)$, at each iteration. Even for Gaussian distributions, this quantity cannot be obtained in closed form, while the Rényi divergence between Gaussians can be computed exactly. In this section, we provide an upper bound for computing the exponentiated Rényi divergence between a generic distribution and a mixture.

Theorem 4.1.1. *Let P be a probability measure and $\Phi = \sum_{k=1}^K \beta_k Q_k$, with $\beta_k \in [0, 1]$ and $\sum_{k=1}^K \beta_k = 1$, be a finite mixture of the probability measures $\{Q_k\}_{k=1}^K$. Then, for any $\alpha \geq 1$, the exponentiated α -Rényi divergence can be bounded as:*

$$d_{\alpha}(P \parallel \Phi) \leq \frac{1}{\sum_{k=1}^K \frac{\beta_k}{d_{\alpha}(P \parallel Q_k)}}. \quad (4.3)$$

The proof can be found in [Appendix A](#). We can easily compute this upper bound of the exponentiated Rényi divergence between the target distribution and the mixture of behavioural distributions. In fact, all the hyperpolicies employed are multivariate diagonal Gaussian distributions, and the Rényi divergence between multivariate Gaussian distributions is known [\[47\]](#). Let $P \sim \mathcal{N}(\boldsymbol{\mu}_P, \boldsymbol{\Sigma}_P)$ and $Q \sim \mathcal{N}(\boldsymbol{\mu}_Q, \boldsymbol{\Sigma}_Q)$ and $\alpha \in [0, \infty]$:

$$D_\alpha(P||Q) = \frac{1}{\alpha}(\boldsymbol{\mu}_P - \boldsymbol{\mu}_Q)^T \boldsymbol{\Sigma}_\alpha^{-1}(\boldsymbol{\mu}_P - \boldsymbol{\mu}_Q) - \frac{1}{2(\alpha - 1)} \log \frac{\det(\boldsymbol{\Sigma}_{\alpha})}{\det(\boldsymbol{\Sigma}_P)^{1-\alpha} \det(\boldsymbol{\Sigma}_Q)^\alpha}. \quad (4.4)$$

4.1.2 Uniformly Bounded Rényi divergence

The other concern about the exponentiated Rényi divergence between the target and mixture of behavioural hyperpolicies is to make it compliant with Assumption (3.4.1), i.e., uniformly bounded. Without this assumption, the results on **OPTIMIST** regret are no more guaranteed. This assumption can be easily respected by careful hyperpolicy design. First, note that the results on the regret are provided for a compact arm set, hence the maximum distance among the parameters is bounded. Additionally, we must ensure that the Rényi divergence is bounded. As showed in Theorem (4.1.1), considering the divergence between a target distribution and a mixture of behavioural distributions it is enough that the divergence is finite between the target and one of the components of the mixture, hence we will focus on the constraints between behavioural/target pairs. As an example, for multivariate diagonal Gaussian distributions with fixed covariance there is no such problem, as the Renyi divergence is a continuous function of the mean parameter [47]. As we know, a continuous function on a compact set is bounded. If the standard deviation (or covariance matrix) is also part of the parameter set, additional constraints are needed, as one can understand by examining Equation (??). For $\epsilon = 1$, the standard deviation σ_P of the target distribution must not be larger than twice that of the behavioural (σ_Q) for the divergence to be finite. Hence, given a minimum $\sigma_0 > 0$, it is enough to constrain the search within $[\sigma_0, 2 * \sigma_0]$. We also suggest initializing the first behavioural distribution with $\sigma_Q = 2 * \sigma_0$, so that the algorithm will move towards smaller standard deviations. This will result in a less stochastic behaviour. Similar constraints can be defined for other kinds of policies [47].

4.2 Action-based setting

The reader may wonder why we did not carry out numerical simulations in the *action-based* setting. Actually, we did make some experiments, but we briefly understood that there was a major obstacle represented by the computation of the Rényi divergence. In fact, although what has been discussed in this section

apply also to the policies (not only hyperpolicies), the loss function can not be directly optimized since computing $d_{1+\epsilon}(p_{\mathbf{x}}\|\Phi_t)$ requires the approximation of an integral over the trajectory space and, for stochastic environments, to know the transition model \mathcal{P} , which is unknown in a model free setting. For the sake of clarity, we report here the definition of the Rényi divergence between the distributions $p_{\theta'}(\tau)$ and $p_{\theta}(\tau)$ over trajectories $\tau \in \mathcal{T}$, induced by the target $(\pi_{\theta'})$ and behavioural (π_{θ}) policies: [1.41](#)

$$d_{\alpha}(p_{\theta'}|p_{\theta}) = \left(\int_{\mathcal{T}} p_{\theta}(\tau) \left(\frac{p_{\theta'}(\tau)}{p_{\theta}(\tau)} \right)^{\alpha} d\tau \right)^{\frac{1}{\alpha-1}}. \quad (4.5)$$

Simple bounds to this quantity, like $d_{\alpha}(p_{\theta'}|p_{\theta}) \leq \sup_{s \in \mathcal{S}} d_{\alpha}(\pi_{\theta'}(\cdot|s)|\pi_{\theta}(\cdot|s))$, besides being hard to compute due to the presence of the supremum, are extremely conservative since the Rényi divergence is raised to the horizon H . In our experiments, we tested [OPTIMIST](#) over the [LQG](#) problem by estimating the exponentiated 2-Rényi divergence between a proposal (Q) and a target (P) distribution as follows:

$$d_2(P|Q) = t/\widehat{ESS} \quad (4.6)$$

where t is the number of samples available, which in our case corresponds to the iteration step number, $w_{P/Q}$ is the importance weight, and \widehat{ESS} [\[75\]](#) is a well known estimator of the *effective sample size*(ESS) [\[66\]](#), given by:

$$\widehat{ESS} = \frac{\|w_{P/Q}\|_1^2}{\|w_{P/Q}\|_2^2} \quad (4.7)$$

Ideed, the effective sample size is defined as [\[66\]](#)

$$ESS = \frac{t}{\mathbb{V}\text{ar}_{x \sim Q}[w_{P/Q}(x)] + 1} = \frac{t}{d_2(P|Q)}. \quad (4.8)$$

However, its estimator \widehat{ESS} is very rough and turned out to be useless in our case. As we show in Figure (BOOO), the main problem about \widehat{ESS} was that it did not allow to share the information obtained by a behavioural Q with distant target distributions P ...Moreover, by estimating the the Rényi from the samples we would lose our theoretical guarantees on the regret.

4.3 Linear Quadratic Gaussian Regulator

The goal of our numerical simulations on **LQG** is twofold. First, we need a simple continuous control problem to understand the functioning of our algorithms. Second, we want to compare **OPTIMIST** with two classical **MAB** algorithms presented in Chapter (2): **UCB1** (2.1.2) and **GPUCB** (2.4), in the case of discrete parameter space Ξ .

The **LQG** problem [98] is a continuous **MDP** which represents a useful testing ground for our algorithms, mainly because of its simplicity. At each time-step h , the transition kernel and reward function are given by:

$$\mathbf{s}_{h+1} = \mathbf{A}\mathbf{s}_h + \mathbf{B}\mathbf{a}_h + \boldsymbol{\eta}_h \quad (4.9)$$

$$r_h = \mathbf{s}_h^T \mathbf{Q} \mathbf{s}_h + \mathbf{a}_h^T \mathbf{R} \mathbf{a}_h \quad (4.10)$$

where \mathbf{A} , \mathbf{B} , \mathbf{Q} and \mathbf{R} are coefficient matrices and $\boldsymbol{\eta}_h$ is a noise process assumed to be a Gaussian white noise $\boldsymbol{\eta}_h \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{LQG})$ with uncorrelated components $\boldsymbol{\Sigma}_{LQG} = \sigma_{LQG} \mathbf{I}$. The reward r_h has to be intended as a cost for the agent, something it wants to avoid. Intuitively, in this problem the agent has to bring its state to zero, while facing a cost proportional to the magnitude of its state and action. The optimal control policy in steady state conditions is the linear controller $\mathbf{a}_h = \mathbf{K}\mathbf{s}_h$, where matrix \mathbf{K} can be found by solving a Riccati equation [43]. We conducted our experiments on one-dimensional **LQG**. For implementation reasons, we consider the case in which the state space is limited to $\mathcal{S} = [-4, 4]$, the action space is $\mathcal{A} = [-4, 4]$ and the horizon is limited to $H = 20$. As mentioned in the previous section, in all our experiments we employ diagonal Gaussian hyperpolicies. In this case the hyperpolicy is univariate $\nu_{\boldsymbol{\xi}} = \mathcal{N}(\mu, \sigma^2)$, where μ is the mean parameter to be learned and σ can be either fixed or learnable as well. On the other hand, the policy π_{θ} adopted by the agent is a deterministic linear controller $a_h = \pi_{\theta}(s_h) = \theta s_h$, with $\theta \sim \nu_{\boldsymbol{\xi}}$. Since **UCB1** requires a positive return $r_t \in [0, 1]$, we standardized the trajectory return $\mathcal{R}(\boldsymbol{\xi}_t) = \sum_{h=0}^{H-1} \gamma^h r_{h+1}$ associated to the arm $\boldsymbol{\xi}_t$ pulled at iteration t :

$$r_t = \mathcal{R}(\boldsymbol{\xi}_t) / \mathcal{R}(\boldsymbol{\xi}^*), \quad (4.11)$$

where $\boldsymbol{\xi}^*$ is the optimal arm and $\mathcal{R}(\boldsymbol{\xi}^*)$ is:

a	b	q	r	σ_{LQG}	γ
1.00	1.00	0.90	0.90	0.10	0.99

Table 4.1: Coefficients of the **LQG** experiments.

$$\mathcal{R}(\boldsymbol{\xi}^*) = \sum_{h=0}^{H-1} \gamma^h \cdot 1 = \frac{1 - \gamma^H}{1 - \gamma}. \quad (4.12)$$

The values of the coefficients used in the experiments are reported in Table (4.1).

In order to benchmark **OPTIMIST** with both **UCB1** and **GPUCB** on a discrete set, we consider a uniform discretization of the interval $[-1, 1]$ made of 100 arms. All algorithms are run with confidence level $\delta = 0.2$.

In Figure 4.1, we show the cumulative regret of the three algorithms, averaged over 30 runs. We can see that our algorithm significantly outperforms **UCB1**. Indeed, **OPTIMIST** is able to exploit the structure of arms, i.e., hyperpolicies, by means of the **MIS** estimation, whereas **UCB1** does not make any assumption on arm correlation. In other words, **OPTIMIST** performs a more informed, i.e., directed, exploration, leveraging what the agent has experienced in past episodes more effectively. On the contrary, **GPUCB** shows a better performance w.r.t. to **OPTIMIST**. We point out that **GPUCB** requires to specify, at the beginning of learning, the kernel of the Gaussian process from which the payoff function is sampled. We employed the default scikit-learn³ kernel, i.e., the radial basis function kernel of the form:

$$k_T(\mathbf{x}, \mathbf{x}') = \exp\left(-\lambda \|\mathbf{x} - \mathbf{x}'\|^2\right), \quad (4.13)$$

where λ is a free parameter. However, as it often happens in control tasks, our payoff is not actually sampled from a Gaussian process. This invalidates all theoretical guarantees of **GPUCB** and may be at the root of the significantly more exploitative behavior w.r.t. **UCB1** and **OPTIMIST** in the experiment. Indeed, the exploration effort of the different algorithms is vi

³A popular library for data mining and data analysis. Available at: <https://scikit-learn.org/stable/>

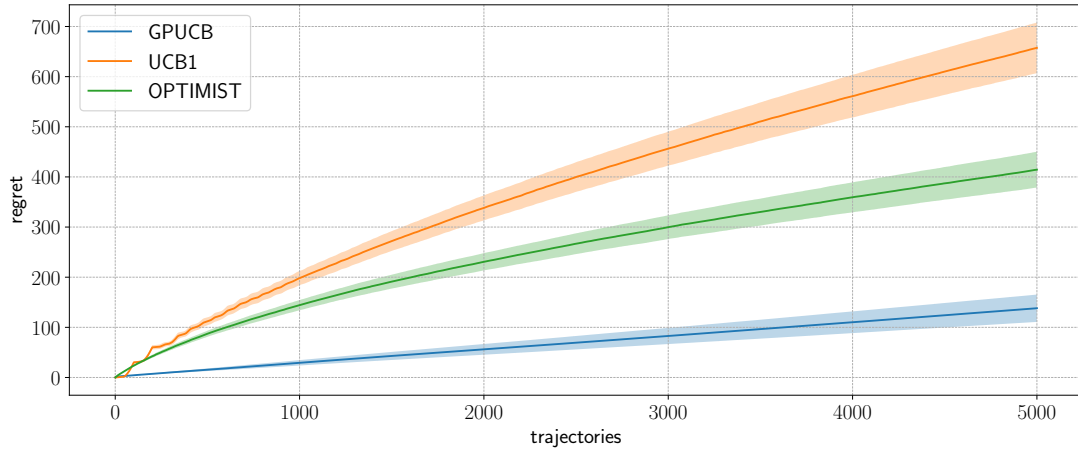


Figure 4.1: Cumulative regret in the **LQG** experiment, comparing **OPTIMIST**, **UCB1** and **GPUCB** (30 runs, 95% c.i.)

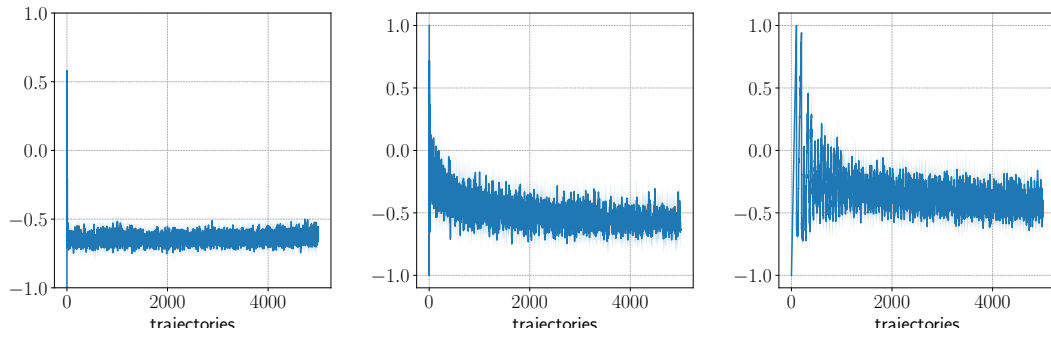


Figure 4.2: The gain parameter $\mu \in \xi$ selected at each iteration of (\cdot) , (\cdot) and (\cdot)

- (i) explain how and why rewards have been rescaled
- (ii) show figures with gain oscillations
- (iii) maybe show other tensor-board plots of the bound and shit?
- (iv) what happened when changing variance???

Appendix A

Proofs

Lemma 1.5.1. *Let P and $\{Q_k\}_{k=1}^K$ be probability measures on the measurable space $(\mathcal{Z}, \mathcal{F})$ such that $P \ll Q_k$ and $d_2(P\|Q_k) < \infty$ for $k = 1, \dots, K$. Let $f : \mathcal{Z} \rightarrow \mathbb{R}$ be a bounded function, i.e., $\|f\|_\infty < \infty$. Let $\hat{\mu}_{BH}$ be the balance heuristic estimator of f , as defined in (1.40), using N_k i.i.d. samples from each Q_k . Then, the variance of $\hat{\mu}_{BH}$ can be upper bounded as:*

$$\text{Var}_{z_{ik} \stackrel{iid}{\sim} Q_k} [\hat{\mu}_{BH}] \leq \|f\|_\infty^2 \frac{d_2(P\|\Phi)}{N}, \quad (1.44)$$

where $N = \sum_{k=1}^K N_k$ is the total number of samples and $\Phi = \sum_{k=1}^K \frac{N_k}{N} Q_k$ is a finite mixture.

Proof. The proof is similar to Lemma 4.1 of [80]:

$$\begin{aligned} \mathbb{V}\text{ar}_{z_{ik} \sim Q_k} [\hat{\mu}_{BH}] &= \mathbb{V}\text{ar}_{z_{ik} \sim Q_k} \left[\frac{1}{N} \sum_{k=1}^K \sum_{i=1}^{N_k} f(z_{ki}) \frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right] \\ &= \frac{1}{N^2} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{V}\text{ar}_{z_{ik} \sim Q_k} \left[f(z_{ki}) \frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right] \end{aligned} \quad (\text{A.1})$$

$$\begin{aligned} &\leq \frac{1}{N^2} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{E}_{z_{ik} \sim Q_k} \left[\left(f(z_{ki}) \frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right)^2 \right] \\ &\leq \|f\|_\infty \frac{1}{N^2} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{E}_{z_{ik} \sim Q_k} \left[\left(\frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right)^2 \right] \\ &= \|f\|_\infty^2 \frac{1}{N} \mathbb{E}_{z \sim \Phi} \left[\left(\frac{p(z)}{\sum_{j=1}^n \frac{N_j}{N} q_j(z)} \right)^2 \right] \quad (\text{A.2}) \\ &= \|f\|_\infty^2 \frac{d_2(P\|\Phi)}{N}, \end{aligned}$$

where (A.1) follows from the independence of the z_{ik} and (A.2) is obtained by the definition of Φ and observing that for an arbitrary function g :

$$\frac{1}{N} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{E}_{z_{ik} \sim Q_k} [g(z_{ik})] = \sum_{k=1}^K \frac{N_k}{N} \mathbb{E}_{z_{1k} \sim Q_k} [g(z_{1k})] = \mathbb{E}_{z \sim \Phi} [g(z)]. \quad (\text{A.3})$$

□

Lemma 3.1.1. *Let P and $\{Q_k\}_{k=1}^N$ be probability measures on the measurable space $(\mathcal{Z}, \mathcal{F})$ such that $P \ll Q_k$ and there exists $\epsilon \in (0, 1]$ s.t. $d_{1+\epsilon}(P\|Q_k) < \infty$ for $k = 1, \dots, K$. Let $f : \mathcal{Z} \rightarrow \mathbb{R}_+$ be a bounded non-negative function, i.e., $\|f\|_\infty < \infty$. Let $\check{\mu}_{BH}$ be the truncated balance heuristic estimator of f , as defined in (3.2), using N_k i.i.d. samples from each Q_k . Then, the bias of $\check{\mu}_{BH}$ can be bounded as:*

$$0 \leq \mu - \mathbb{E}_{z_{ik} \sim Q_k} [\check{\mu}_{BH}] \leq \|f\|_\infty M^{-\epsilon} d_{1+\epsilon}(P\|\Phi)^\epsilon, \quad (3.3)$$

and the variance of $\check{\mu}_{BH}$ can be bounded as:

$$\mathbb{V}\text{ar}_{z_{ik} \sim Q_k} [\check{\mu}_{BH}] \leq \|f\|_\infty^2 M^{1-\epsilon} \frac{d_{1+\epsilon}(P\|\Phi)^\epsilon}{N}, \quad (3.4)$$

where $N = \sum_{k=1}^K N_k$ is the total number of samples and $\Phi = \sum_{k=1}^K \frac{N_k}{N} Q_k$ is a finite mixture.

Proof. Let us start with the bias term. The first inequality $0 \leq \mu - \mathbb{E}_{z_{ik} \sim Q_k} [\tilde{\mu}_{\text{BH}}]$ derives from the fact that $\hat{\mu}_{\text{BH}} \geq \tilde{\mu}_{\text{BH}}$, being $f(z) \geq 0$ for all z and observing that $\hat{\mu}$ is unbiased, i.e., $\mathbb{E}_{z_{ik} \sim Q_k} [\hat{\mu}_{\text{BH}}] = \mu$. For the second inequality, let us consider the following derivation:

$$\begin{aligned} \mu - \mathbb{E}_{x_i \sim q_i} [\tilde{\mu}] &= \mathbb{E}_{z_{ik} \sim Q_k} [\hat{\mu}_{\text{BH}}] - \mathbb{E}_{z_{ik} \sim Q_k} [\tilde{\mu}_{\text{BH}}] \\ &= \frac{1}{N} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{E}_{z_{ik} \sim Q_k} \left[f(z_{ik}) \left(\frac{p(z_{ik})}{\sum_{j=1}^K \frac{N_j}{N} q_j(z_{ik})} - \min \left\{ M, \frac{p(z_{ik})}{\sum_{j=1}^K \frac{N_j}{N} q_j(z_{ik})} \right\} \right) \right] \end{aligned} \quad (\text{A.4})$$

$$= \mathbb{E}_{z \sim \Phi} \left[f(z) \left(\frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} - M \right) \mathbb{1}_{\left\{ \frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \geq M \right\}} \right] \quad (\text{A.5})$$

$$\leq \mathbb{E}_{z \sim \Phi} \left[f(z) \left(\frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \right) \mathbb{1}_{\left\{ \frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \geq M \right\}} \right] \quad (\text{A.6})$$

$$\begin{aligned} &\leq \|f\|_{\infty} \mathbb{E}_{z \sim \Phi} \left[\left(\frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \right) \mathbb{1}_{\left\{ \frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \geq M \right\}} \right] \\ &\leq \|f\|_{\infty} \mathbb{E}_{z \sim \Phi} \left[\left(\frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \right)^{1+\epsilon} \left(\frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \right)^{-\epsilon} \mathbb{1}_{\left\{ \frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \geq M \right\}} \right] \\ &\leq \|f\|_{\infty} \mathbb{E}_{z \sim \Phi} \left[\left(\frac{p(z)}{\sum_{j=1}^K \frac{N_j}{N} q_j(z)} \right)^{1+\epsilon} \right] M^{-\epsilon} \quad (\text{A.7}) \\ &= \|f\|_{\infty} d_{1+\epsilon}(P \|\Phi)^{\epsilon} M^{-\epsilon}, \end{aligned}$$

where (A.5) is an application of equation (A.3), (A.6) derives from recalling that $M \geq 0$ and (A.7) is obtained by observing that $x^{-\epsilon} \mathbb{1}_{\{x \geq M\}}$ is either 0 and thus

the bound holds or at most $M^{-\epsilon}$. For the variance the argument is similar:

$$\begin{aligned}
 \mathbb{V}\text{ar}_{z_{ik} \sim Q_k} [\check{\mu}_{BH}] &= \mathbb{V}\text{ar}_{z_{ik} \sim Q_k} \left[\frac{1}{N} \sum_{k=1}^K \sum_{i=1}^{N_k} f(z_{ki}) \min \left\{ M, \frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right\} \right] \\
 &= \frac{1}{N^2} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{V}\text{ar}_{z_{ik} \sim Q_k} \left[f(z_{ki}) \min \left\{ M, \frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right\} \right] \\
 &\leq \frac{1}{N^2} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{E}_{z_{ik} \sim Q_k} \left[\left(f(z_{ki}) \min \left\{ M, \frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right\} \right)^2 \right] \\
 &\leq \|f\|_\infty \frac{1}{N^2} \sum_{k=1}^K \sum_{i=1}^{N_k} \mathbb{E}_{z_{ik} \sim Q_k} \left[\left(\min \left\{ M, \frac{p(z_{ki})}{\sum_{j=1}^n \frac{N_j}{N} q_j(z_{ki})} \right\} \right)^2 \right] \\
 &= \|f\|_\infty^2 \frac{1}{N} \mathbb{E}_{z \sim \Phi} \left[\min \left\{ M, \frac{p(z)}{\sum_{j=1}^n \frac{N_j}{N} q_j(z)} \right\}^2 \right] \tag{A.8}
 \end{aligned}$$

$$\begin{aligned}
 &= \|f\|_\infty^2 \frac{1}{N} \mathbb{E}_{z \sim \Phi} \left[\min \left\{ M, \frac{p(z)}{\sum_{j=1}^n \frac{N_j}{N} q_j(z)} \right\}^{1+\epsilon} \min \left\{ M, \frac{p(z)}{\sum_{j=1}^n \frac{N_j}{N} q_j(z)} \right\}^{1-\epsilon} \right] \\
 &\leq \|f\|_\infty^2 \frac{1}{N} \mathbb{E}_{z \sim \Phi} \left[\left(\frac{p(z)}{\sum_{j=1}^n \frac{N_j}{N} q_j(z)} \right)^{1+\epsilon} \right] M^{1-\epsilon} \tag{A.9}
 \end{aligned}$$

$$= \|f\|_\infty^2 M^{1-\epsilon} \frac{d_{1+\epsilon}(P\|\Phi)^\epsilon}{N}, \tag{A.10}$$

where (A.8) is again an application of equation (A.3) and A.9 derives from observing that $\min\{x, y\} \leq x$ and also $\min\{x, y\} \leq y$. \square

Theorem 3.1.1. *Let P and $\{Q_k\}_{k=1}^N$ be probability measures on the measurable space $(\mathcal{Z}, \mathcal{F})$ such that $P \ll Q_k$ and there exists $\epsilon \in (0, 1]$ s.t. $d_{1+\epsilon}(P\|Q_k) < \infty$ for $k = 1, \dots, K$. Let $f : \mathcal{Z} \rightarrow \mathbb{R}_+$ be a bounded non-negative function, i.e., $\|f\|_\infty < \infty$. Let $\check{\mu}_{BH}$ be the truncated balance heuristic estimator of f , as defined in (3.2), using N_k i.i.d. samples from each Q_k . Let $M_N = \left(\frac{Nd_{1+\epsilon}(P\|\Phi)^\epsilon}{\log \frac{1}{\delta}} \right)^{\frac{1}{1+\epsilon}}$, then with probability at least $1 - \delta$:*

$$\check{\mu}_{BH} \leq \mu + \|f\|_\infty \left(\sqrt{2} + \frac{1}{3} \right) \left(\frac{d_{1+\epsilon}(P\|\Phi) \log \frac{1}{\delta}}{N} \right)^{\frac{\epsilon}{1+\epsilon}}, \tag{3.5}$$

and also, with probability at least $1 - \delta$:

$$\check{\mu}_{BH} \geq \mu - \|f\|_\infty \left(\sqrt{2} + \frac{4}{3} \right) \left(\frac{d_{1+\epsilon}(P\|\Phi) \log \frac{1}{\delta}}{N} \right)^{\frac{\epsilon}{1+\epsilon}}. \tag{3.6}$$

Proof. Let us start with the first inequality. Observing that all samples z_{ik} are independent and that $\check{\mu}_{\text{BH}} \leq M\|f\|_\infty$, we can state using Bernstein inequality [21] that with probability at least $1 - \delta$ we have:

$$\begin{aligned} \check{\mu}_{\text{BH}} &\leq \mathbb{E}_{z_{ik} \sim Q_k} [\check{\mu}_{\text{BH}}] + \sqrt{2 \mathbb{Var}_{z_{ik} \stackrel{\text{iid}}{\sim} Q_k} [\check{\mu}_{\text{BH}}] \log \frac{1}{\delta}} + \|f\|_\infty \frac{M \log \frac{1}{\delta}}{3N} \\ &\leq \mu + \|f\|_\infty \sqrt{\frac{2M^{1-\epsilon} d_{1+\epsilon} (P\|\Phi\|^\epsilon \log \frac{1}{\delta})}{N}} + \|f\|_\infty \frac{M \log \frac{1}{\delta}}{3N} \end{aligned} \quad (\text{A.11})$$

$$= \mu + \|f\|_\infty \left(\sqrt{2} + \frac{1}{3} \right) \left(\frac{d_{1+\epsilon} (P\|\Phi\|^\epsilon \log \frac{1}{\delta})}{N} \right)^{\frac{\epsilon}{1+\epsilon}}, \quad (\text{A.12})$$

where (A.11) is obtained by substituting the variance with its bound (3.4) and (A.12) is from the choice of M . For the second inequality we just need to consider additionally the bias.

$$\begin{aligned} \check{\mu}_{\text{BH}} &\geq \mathbb{E}_{z_{ik} \sim Q_k} [\check{\mu}_{\text{BH}}] - \sqrt{2 \mathbb{Var}_{z_{ik} \stackrel{\text{iid}}{\sim} Q_k} [\check{\mu}_{\text{BH}}] \log \frac{1}{\delta}} - \|f\|_\infty \frac{M \log \frac{1}{\delta}}{3N} \\ &= \mu - \left(\mu - \mathbb{E}_{z_{ik} \sim Q_k} [\check{\mu}_{\text{BH}}] \right) - \sqrt{2 \mathbb{Var}_{z_{ik} \stackrel{\text{iid}}{\sim} Q_k} [\check{\mu}_{\text{BH}}] \log \frac{1}{\delta}} - \|f\|_\infty \frac{M \log \frac{1}{\delta}}{3N} \\ &\geq \mu - \|f\|_\infty M^{-\epsilon} d_{1+\epsilon} (P\|\Phi\|^\epsilon) - \|f\|_\infty \left(\sqrt{2} + \frac{1}{3} \right) \left(\frac{d_{1+\epsilon} (P\|\Phi\|^\epsilon \log \frac{1}{\delta})}{N} \right)^{\frac{\epsilon}{1+\epsilon}} \end{aligned} \quad (\text{A.13})$$

$$= \mu - \|f\|_\infty \left(\sqrt{2} + \frac{4}{3} \right) \left(\frac{d_{1+\epsilon} (P\|\Phi\|^\epsilon \log \frac{1}{\delta})}{N} \right)^{\frac{\epsilon}{1+\epsilon}}, \quad (\text{A.14})$$

where (A.13) comes from substituting the bias with its bound (3.3). \square

Theorem 3.4.1. *Let \mathcal{X} be a discrete arm set with $|\mathcal{X}| = K \in \mathbb{N}_+$. Under Assumption (3.4.1), Algorithm (3.1) with confidence schedule $\delta_t = \frac{3\delta}{t^2 \pi^2 K}$ guarantees, with probability at least $1 - \delta$:*

$$\begin{aligned} \text{Regret}(T) &\leq \Delta_0 \\ &\quad + CT^{\frac{1}{1+\epsilon}} \left[v_\epsilon \left(2 \log T + \log \frac{\pi^2 K}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}}, \end{aligned}$$

where $C = (1 + \epsilon) \left(2\sqrt{2} + \frac{5}{3} \right) \|f\|_\infty$, and Δ_0 is the instantaneous regret of the initial arm \mathbf{x}_0 .

Proof. Fix an $\epsilon > 0$. To ease the notation, let $c^- := \|f\|_\infty \left(\sqrt{2} + \frac{1}{3} \right)$, $c^+ := \|f\|_\infty \left(\sqrt{2} + \frac{4}{3} \right)$, and $\beta_t(\mathbf{x}) := \left(\frac{d_{1+\epsilon}(p_{\mathbf{x}}\|\Phi_t\|^\epsilon \log \frac{1}{\delta_t})}{t} \right)^{\frac{\epsilon}{1+\epsilon}}$. We start by showing that,

with probability at least $1 - \delta$:

$$-c^+ \beta_t(\mathbf{x}) \leq \check{\mu}_t(\mathbf{x}) - \mu(\mathbf{x}) \leq c^- \beta_t(\mathbf{x}) \quad \text{for all } \mathbf{x} \in \mathcal{X} \text{ and } t = 1, \dots, T. \quad (\text{A.15})$$

Indeed:

$$\begin{aligned} \mathbb{P} \left(\bigcap_{k=1}^K \bigcap_{t=1}^T [\check{\mu}_t(\mathbf{x}_k) - \mu(\mathbf{x}_k) \leq c^- \beta_t(\mathbf{x}_k)] \right) &= 1 - \mathbb{P} \left(\bigcup_{k=1}^K \bigcup_{t=1}^T [\check{\mu}_t(\mathbf{x}_k) - \mu(\mathbf{x}_k) > c^- \beta_t(\mathbf{x}_k)] \right) \\ &\geq 1 - K \sum_{t=1}^T \mathbb{P}(\check{\mu}_t(\mathbf{x}_1) - \mu(\mathbf{x}_1) > c^- \beta_t(\mathbf{x}_1)) \end{aligned} \quad (\text{A.16})$$

$$\geq 1 - K \sum_{t=1}^T \delta_t \quad (\text{A.17})$$

$$\geq 1 - \frac{\delta}{2}, \quad (\text{A.18})$$

where (A.16) is from a double union bound (over time and over the finite elements of \mathcal{X}), (A.17) is from Theorem 3.1.1, and (A.18) is by hypothesis on δ_t and $\sum_{t=1}^T \frac{1}{t^2} \leq \sum_{t=1}^{\infty} \frac{1}{t^2} = \frac{\pi^2}{6}$. Similarly:

$$\begin{aligned} \mathbb{P} \left(\bigcap_{k=1}^K \bigcap_{t=1}^T [\check{\mu}_t(\mathbf{x}_k) - \mu(\mathbf{x}_k) \geq -c^+ \beta_t(\mathbf{x}_k)] \right) &= 1 - \mathbb{P} \left(\bigcup_{k=1}^K \bigcup_{t=1}^T [\check{\mu}_t(\mathbf{x}_k) - \mu(\mathbf{x}_k) < -c^+ \beta_t(\mathbf{x}_k)] \right) \\ &\geq 1 - K \sum_{t=1}^T \mathbb{P}(\check{\mu}_t(\mathbf{x}_1) - \mu(\mathbf{x}_1) < -c^+ \beta_t(\mathbf{x}_1)) \\ &\geq 1 - K \sum_{t=1}^T \delta_t \\ &\geq 1 - \frac{\delta}{2}. \end{aligned}$$

Hence, by union bound over the two inequalities, (A.15) holds with probability at least $1 - \delta$. This allows to lower bound the instantaneous regret with the same probability:

$$\Delta_t = \mu(\mathbf{x}^*) - \mu(\mathbf{x}) \leq \check{\mu}_t(\mathbf{x}^*) + c^+ \beta_t(\mathbf{x}^*) - \mu(\mathbf{x}_t) \quad (\text{A.19})$$

$$\leq \check{\mu}_t(\mathbf{x}_t) + c^+ \beta_t(\mathbf{x}_t) - \mu(\mathbf{x}_t) \quad (\text{A.20})$$

$$\leq (c^- + c^+) \beta_t(\mathbf{x}_t) \quad \text{for all } t = 1, \dots, T, \quad (\text{A.21})$$

where (A.19) and (A.21) are from (A.15), while (A.20) is by hypothesis, as $\mathbf{x}_t = \arg \max_{\mathbf{x} \in \mathcal{X}} (\check{\mu}_t(\mathbf{x}) + c^+ \beta_t(\mathbf{x}))$. Note that the union bound over the elements of \mathcal{X} in (A.15) was necessary for (A.19) as the optimal arm \mathbf{x}^* may not be unique.

Finally, with probability at least $1 - \delta$:

$$\begin{aligned} \text{Regret}(T) &= \sum_{t=0}^T \Delta_t \\ &= \Delta_0 + \sum_{t=1}^T \Delta_t \\ &\leq \Delta_0 + (c^+ + c^-) \sum_{t=1}^T \beta_t(\mathbf{x}_t) \end{aligned} \quad (\text{A.22})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{\log \frac{1}{\delta_t}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} \quad (\text{A.23})$$

$$= \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{2 \log t + \log \frac{\pi^2 K}{3\delta}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} \quad (\text{A.24})$$

$$\begin{aligned} &\leq \Delta_0 + (c^+ + c^-) \left[v_\epsilon \left(2 \log T + \log \frac{\pi^2 K}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T t^{-\frac{\epsilon}{1+\epsilon}} \\ &\leq \Delta_0 + (c^+ + c^-) \left[v_\epsilon \left(2 \log T + \log \frac{\pi^2 K}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} (1 + \epsilon) T^{\frac{1}{1+\epsilon}}, \end{aligned} \quad (\text{A.25})$$

where (A.22) is from (A.21) and holds with probability no less than $1 - \delta$, (A.23) is from Assumption 3.4.1, (A.24) is by definition of δ_t , and (A.25) is from:

$$\sum_{t=1}^T t^{-\alpha} \leq \int_1^{T+1} t^{-\alpha} dt = \frac{1}{1-\alpha} ((T+1)^{1-\alpha} - 1) \leq \frac{T^{1-\alpha}}{1-\alpha} \quad \text{for all } 0 < \alpha < 1, \quad (\text{A.26})$$

with $\alpha = \frac{\epsilon}{1+\epsilon}$. The proof is completed by renaming $C \leftarrow (1 + \epsilon)(c^+ + c^-) = (1 + \epsilon)(2\sqrt{2} + \frac{5}{3}) \|f\|_\infty$. \square

Lemma 3.4.1. *In the policy optimization problem, Assumption 3.4.2 can be replaced by:*

$$\sup_{s \in \mathcal{S}, \theta \in \Theta} \mathbb{E}_{a \sim \pi_\theta} [|\nabla_\theta \log \pi_\theta(a|s)|] \leq \mathbf{u}_1, \quad (3.12)$$

in the action-based paradigm, and by:

$$\sup_{\xi \in \Xi} \mathbb{E}_{\theta \sim \rho_\xi} [|\nabla_\xi \log \rho_\xi(\theta)|] \leq \mathbf{u}_2, \quad (3.13)$$

in the parameter-based paradigm, where \mathbf{u}_1 and \mathbf{u}_2 are d -dimensional vectors and the inequalities are component-wise.

Proof. We consider the infinite-horizon case ($H = \infty, \gamma < 1$), as the finite-horizon case is w.l.o.g. under mild assumptions. To show Lipschitz continuity in the

action-based paradigm, it is enough to bound $\|\nabla_{\boldsymbol{\theta}} J\|_{\infty}$ under (3.12). From the Policy Gradient Theorem [120]:

$$\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}) = \frac{1}{1-\gamma} \mathbb{E}_{\substack{s \sim \rho_{\boldsymbol{\theta}} \\ a \sim \pi_{\boldsymbol{\theta}}}} [\nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a|s) Q_{\boldsymbol{\theta}}(s, a)], \quad (\text{A.27})$$

where $\rho_{\boldsymbol{\theta}}$ is the discounted state-occupancy measure under policy $\pi_{\boldsymbol{\theta}}$ and $Q_{\boldsymbol{\theta}}$ is the action-value function [120], modeling the reward that can be obtained starting from state s , taking action a and following $\pi_{\boldsymbol{\theta}}$ thereafter. From (A.27), for every $\boldsymbol{\theta} \in \Theta$:

$$|\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta})| \leq \frac{R_{\max}}{(1-\gamma)^2} \mathbb{E}_{\substack{s \sim \rho_{\boldsymbol{\theta}} \\ a \sim \pi_{\boldsymbol{\theta}}}} [|\nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(s, a)|] \quad (\text{A.28})$$

$$\begin{aligned} &\leq \frac{R_{\max}}{(1-\gamma)^2} \sup_{s \in \mathcal{S}} \mathbb{E}_{a \sim \pi_{\boldsymbol{\theta}}} [|\nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(s, a)|] \\ &= \frac{\mathbf{u}_1 R_{\max}}{(1-\gamma)^2}, \end{aligned} \quad (\text{A.29})$$

where the inequalities are component-wise, (A.28) is from the trivial fact $\|Q_{\boldsymbol{\theta}}\|_{\infty} \leq \frac{R_{\max}}{(1-\gamma)}$, and (A.29) is from assumption (3.12). It follows that $L = \frac{\|\mathbf{u}_1\|_{\infty} R_{\max}}{(1-\gamma)^2}$ is a valid Lipschitz constant under the l_1 norm. The commonly used Gaussian policy:

$$\pi_{\boldsymbol{\theta}}(a|s) = \mathcal{N}(\boldsymbol{\theta}^T \boldsymbol{\phi}(s), \sigma^2) = \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ -\frac{1}{2} \left(\frac{a - \boldsymbol{\theta}^T \boldsymbol{\phi}(s)}{\sigma} \right)^2 \right\}, \quad (\text{A.30})$$

where $\boldsymbol{\phi}(s)$ is a vector of component-wise bounded state features, i.e., $\sup_{s \in \mathcal{S}} |\boldsymbol{\phi}(s)| \leq \boldsymbol{\phi}_{\max}$, satisfies assumption (3.12):

$$\begin{aligned} \mathbb{E}_{a \sim \pi_{\boldsymbol{\theta}}} [|\nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(a|s)|] &= \mathbb{E}_{a \sim \pi_{\boldsymbol{\theta}}} \left[\frac{|\boldsymbol{\phi}(s)(a - \boldsymbol{\theta}^T \boldsymbol{\phi}(s))|}{\sigma^2} \right] \\ &\leq \frac{|\boldsymbol{\phi}(s)|}{\sigma} \mathbb{E}_{a \sim \pi_{\boldsymbol{\theta}}} \left[\left| \frac{a - \boldsymbol{\theta}^T \boldsymbol{\phi}(s)}{\sigma} \right| \right] \\ &\leq \frac{|\boldsymbol{\phi}(s)|}{\sqrt{2\pi}\sigma} \int_{\mathbb{R}} e^{-x^2} |x| dx \\ &\leq \frac{2\boldsymbol{\phi}_{\max}}{\sqrt{2\pi}\sigma} := \mathbf{u}_1, \end{aligned} \quad (\text{A.31})$$

$$\leq \frac{2\boldsymbol{\phi}_{\max}}{\sqrt{2\pi}\sigma} := \mathbf{u}_1, \quad (\text{A.32})$$

where inequalities are component-wise and (A.31) is by the substitution $x \leftarrow \frac{a - \boldsymbol{\theta}^T \boldsymbol{\phi}(s)}{\sigma}$. Even when σ must be learned, proper parametrization (e.g., $\sigma \propto \exp\{\boldsymbol{\theta}\}$), together with the compactness of Θ , allows to satisfy assumption (3.12).

To show Lipschitz continuity for the parameter-based paradigm, it is enough

to bound $\|\nabla_{\xi} \mathbb{E}_{\theta \sim \rho_{\xi}}[J(\theta)]\|_{\infty}$ under (3.13). For every $\xi \in \Xi$:

$$\begin{aligned} \left| \nabla_{\xi} \mathbb{E}_{\theta \sim \rho_{\xi}}[J(\theta)] \right| &= \left| \mathbb{E}_{\theta \sim \rho_{\xi}} [\nabla_{\xi} \log \rho_{\xi}(\theta) J(\theta)] \right| \\ &\leq \frac{R_{\max}}{(1-\gamma)} \mathbb{E}_{\theta \sim \rho_{\xi}} [|\nabla_{\xi} \log \rho_{\xi}(\theta)|] \end{aligned} \quad (\text{A.33})$$

$$\leq \frac{\mathbf{u}_2 R_{\max}}{(1-\gamma)}, \quad (\text{A.34})$$

where the inequalities are component-wise, (A.33) is from the trivial fact $J(\theta) \leq \frac{R_{\max}}{1-\gamma}$, and (A.34) is from assumption (3.13). It follows that $L = \frac{\|\mathbf{u}_2 R_{\max}\|_{\infty}}{(1-\gamma)}$ is a valid Lipschitz constant under the l_1 norm. A Gaussian hyperpolicy $\rho_{\xi}(\theta) = \mathcal{N}(\xi, \text{diag}(\sigma))$ satisfies assumption (3.13) with $\mathbf{u}_2 = \frac{2}{\sqrt{2\pi}\sigma}$. The proof of this fact is analogous to that of (A.32). Even when σ must be learned, proper parametrization (e.g., $\sigma \propto \exp\{\xi\}$), together with the compactness of Ξ , allows to satisfy assumption (3.13). \square

Theorem 3.4.2. *Let \mathcal{X} be a d -dimensional compact arm set with $\mathcal{X} \subseteq [-D, D]^d$. Under Assumptions (3.4.1) and (3.4.2), Algorithm (3.1) with confidence schedule $\delta_t = \frac{6\delta}{\pi^2 t^2 (1+d^d t^{2d})}$ guarantees, with probability at least $1 - \delta$:*

$$\begin{aligned} \text{Regret}(T) &\leq \Delta_0 \\ &+ CT^{\frac{1}{1+\epsilon}} \left[v_{\epsilon} \left(2(d+1) \log T + d \log d + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} \\ &+ \frac{\pi^2 LD}{6}, \end{aligned}$$

where $C = (1 + \epsilon) (2\sqrt{2} + \frac{5}{3}) \|f\|_{\infty}$, and Δ_0 is the instantaneous regret of the initial arm \mathbf{x}_0 .

Proof. Fix an $\epsilon > 0$. Let c^- , c^+ and $\beta_t(\mathbf{x})$ be defined as in the proof of Theorem 3.4.1. The finite cardinality of \mathcal{X} allowed to perform a union bound over the arms that was crucial for the proof of Theorem 3.4.1. We cannot do the same here as \mathcal{X} has infinite cardinality. To overcome this problem, we follow the line of reasoning proposed by [113]. First, we can say something about the arms that are actually selected by the algorithm, which are finite. From Theorem 3.1.1, by a union bound over $t = 1, \dots, T$, we have that, with probability at least $1 - \sum_{t=1}^T \delta_t$:

$$\check{\mu}_t(\mathbf{x}_t) - \mu(\mathbf{x}_t) \leq c^- \beta_t(\mathbf{x}_t) \quad \text{for all } t = 1, \dots, T. \quad (\text{A.35})$$

We also need a specular inequality for the optimal arm. Unfortunately, we cannot assume there exists a unique optimal arm \mathbf{x}^* .¹ Even worse, a dense set of optimal arms may exist. To overcome this problem, we introduce, *only for the purposes of the proof*, a discretization of the arm space. Let $\tilde{\mathcal{X}}_t$ be a d -dimensional regular grid of τ_t^d vertexes, where $(\tau_t \in \mathbb{N}_+)_{t=1}^T$ is a discretization schedule. Let $[\mathbf{x}]_t$ be the closest vertex to \mathbf{x} in $\tilde{\mathcal{X}}_t$. From Assumption 3.4.2:

$$|\mu(\mathbf{x}) - \mu([\mathbf{x}]_t)| \leq L \|\mathbf{x} - [\mathbf{x}]_t\|_1 \leq \frac{LDd}{\tau_t}, \quad (\text{A.36})$$

as each voxel of the grid has side $\frac{2D}{\tau_t}$ and no point can be further from a vertex than d half-sides according to the l_1 norm. Now fix a $t \geq 1$ and an optimal arm \mathbf{x}^* . With probability at least $1 - \delta_t$:

$$\begin{aligned} \mu(\mathbf{x}^*) - \check{\mu}_t([\mathbf{x}^*]_t) &= \mu(\mathbf{x}^*) - \mu([\mathbf{x}^*]_t) + \mu([\mathbf{x}^*]_t) - \check{\mu}_t([\mathbf{x}^*]_t) \\ &\leq \mu([\mathbf{x}^*]_t) - \check{\mu}_t([\mathbf{x}^*]_t) + |\mu(\mathbf{x}^*) - \mu([\mathbf{x}^*]_t)| \\ &\leq c^+ \beta_t([\mathbf{x}^*]_t) + \frac{LDd}{\tau_t}, \end{aligned} \quad (\text{A.37})$$

where the inequality (A.37) is from Theorem 3.1.1 and (A.36). Since any voxel may contain an optimal arm, we must perform a union bound over the $[\tau]^d$ vertexes of $\tilde{\mathcal{X}}_t$, and a subsequent one over t, \dots, T . Hence, with probability at least $1 - \sum_{t=1}^T \tau_t^d \delta_t$:

$$\mu(\mathbf{x}^*) - \check{\mu}_t([\mathbf{x}^*]_t) \leq c^+ \beta_t([\mathbf{x}^*]_t) + \frac{LDd}{\tau_t} \quad \text{for } t = 1, \dots, T \text{ and every } \mathbf{x}^* \in \arg \max_{\mathbf{x} \in \mathcal{X}} \mu(\mathbf{x}). \quad (\text{A.38})$$

We can now proceed to bound the instantaneous regret. With probability at least $1 - \sum_{t=1}^T \delta_t(1 + \tau_t^d)$:

$$\Delta_t = \mu(\mathbf{x}^*) - \mu(\mathbf{x}_t) \leq \check{\mu}_t([\mathbf{x}^*]_t) + c^+ \beta_t([\mathbf{x}^*]_t) + \frac{LDd}{\tau_t} - \mu(\mathbf{x}_t) \quad (\text{A.39})$$

$$\leq \check{\mu}_t(\mathbf{x}_t) + c^+ \beta_t(\mathbf{x}_t) + \frac{LDd}{\tau_t} - \mu(\mathbf{x}_t) \quad (\text{A.40})$$

$$\leq (c^+ + c^-) \beta_t(\mathbf{x}_t) + \frac{LDd}{\tau_t}, \quad (\text{A.41})$$

where (A.39) is from (A.38) and holds with probability at least $1 - \sum_{t=1}^T \tau_t^d \delta_t$, (A.40) is by hypothesis, as $\mathbf{x}_t = \arg \max_{\mathbf{x} \in \mathcal{X}} (\check{\mu}_t(\mathbf{x}) + c^+ \beta_t(\mathbf{x}))$, and (A.41) is from (A.36) and holds with probability at least $1 - \sum_{t=1}^T \delta_t$. Hence, (A.41) holds with probability no less than $1 - \sum_{t=1}^T \tau_t^d \delta_t - \sum_{t=1}^T \delta_t = 1 - \sum_{t=1}^T \delta_t(1 + \tau_t^d)$. Let us

¹Instead, $\mu(\mathbf{x}^*)$ is always unique.

pick as a discretization schedule $\tau_t = dt^2$. This has no impact whatsoever on the algorithm, as the discretization is only hypothetical. With this τ_t and the confidence schedule proposed in the statement of the theorem, it is easy to verify that (A.41) holds with probability at least $1 - \delta$.

Finally, we can bound the regret. With probability at least $1 - \delta$:

$$\begin{aligned} \text{Regret}(T) &\leq \Delta_0 + \sum_{t=1}^T \Delta_t \\ &\leq \Delta_0 + (c^+ + c^-) \sum_{t=1}^T \beta_t(\mathbf{x}_t) + LDd \sum_{t=1}^T \frac{1}{\tau_t} \end{aligned} \quad (\text{A.42})$$

$$\leq (c^+ + c^-) \sum_{t=1}^T \beta_t(x_t) + \frac{\pi^2 LD}{6} \quad (\text{A.43})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{\log \frac{1}{\delta_t}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\pi^2 LD}{6} \quad (\text{A.44})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{\log(1 + d^d t^{2d}) + 2 \log t + \log \frac{\pi^2}{6\delta}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\pi^2 LD}{6} \quad (\text{A.45})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{\log(2d^d t^{2d}) + 2 \log t + \log \frac{\pi^2}{6\delta}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\pi^2 LD}{6} \quad (\text{A.46})$$

$$\begin{aligned} &= \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{2(d+1) \log t + d \log d + \log \frac{\pi^2}{3\delta}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\pi^2 LD}{6} \\ &\leq \Delta_0 + (c^+ + c^-) \left[v_\epsilon \left(2(d+1) \log T + d \log d + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T t^{-\frac{\epsilon}{1+\epsilon}} + \frac{\pi^2 LD}{6} \\ &\leq \Delta_0 + (c^+ + c^-) \left[v_\epsilon \left(2(d+1) \log T + d \log d + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} (1 + \epsilon) T^{\frac{1}{1+\epsilon}} + \frac{\pi^2 LD}{6}, \end{aligned} \quad (\text{A.47})$$

where (A.42) is from (A.41) and holds with probability at least $1 - \delta$, (A.43) is from the choice of τ_t and $\sum_{t=1}^T t^{-2} \leq \sum_{t=1}^\infty t^{-2} = \frac{\pi^2}{6}$, (A.44) is from Assumption 3.4.1, (A.45) is from the choice of δ_t , (A.46) is from $\log(1 + x) \leq \log(2x)$, which holds for every $x \geq 1$, and (A.47) is from (A.26) with $\alpha = \frac{\epsilon}{1+\epsilon}$. The proof is completed by renaming $C \leftarrow (1 + \epsilon)(c^+ + c^-) = (1 + \epsilon)(2\sqrt{2} + \frac{5}{3}) \|f\|_\infty$. \square

Theorem 3.4.3. *Let \mathcal{X} be a d -dimensional compact arm set with $\mathcal{X} \subseteq [-D, D]^d$. For any $\kappa \geq 2$, under Assumptions (3.4.1) and (3.4.2), Algorithm (3.2) with confidence schedule $\delta_t = \frac{6\delta}{\pi^2 t^2 (1 + \lceil t^{1/\kappa} \rceil^d)}$ and discretization schedule $\tau_t = \lceil t^{\frac{1}{\kappa}} \rceil$ guarantees,*

with probability at least $1 - \delta$:

$$\begin{aligned} \text{Regret}(T) &\leq \Delta_0 + C_1 T^{(1-\frac{1}{\kappa})} d + C_2 T^{\frac{1}{1+\epsilon}} \\ &\quad \cdot \left[v_\epsilon \left((2 + d/\kappa) \log T + d \log 2 + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}}, \end{aligned}$$

where $C_1 = \frac{\kappa}{\kappa-1} LD$, $C_2 = (1 + \epsilon) (2\sqrt{2} + \frac{5}{3}) \|f\|_\infty$, and Δ_0 is the instantaneous regret of the initial arm \mathbf{x}_0 .

Proof. The proof follows the one of Theorem 3.4.2 up to (A.38), except from the fact that the discretization is actually performed by the algorithm. That is, with probability at least $1 - \sum_{t=1}^T \delta_t(1 + \tau_t^d)$:

$$\begin{aligned} \check{\mu}_t(\mathbf{x}_t) - \mu(\mathbf{x}_t) &\leq c^- \beta_t(\mathbf{x}_t) \quad \text{and} \\ \mu(\mathbf{x}^*) - \check{\mu}_t([\mathbf{x}^*]_t) &\leq c^+ \beta_t([\mathbf{x}^*]_t) + \frac{LDd}{\tau_t} \quad \text{for } t = 1, \dots, T \text{ and every } \mathbf{x}^* \in \arg \max_{\mathbf{x} \in \mathcal{X}} \mu(\mathbf{x}). \end{aligned} \quad (\text{A.48})$$

This is enough to bound the instantaneous regret. With probability at least $1 - \sum_{t=1}^T \delta_t(1 + \tau_t^d)$:

$$\Delta_t = \mu(\mathbf{x}^*) - \mu(\mathbf{x}_t) \leq \check{\mu}_t([\mathbf{x}^*]_t) + c^+ \beta_t([\mathbf{x}^*]_t) + \frac{LDd}{\tau_t} - \mu(\mathbf{x}_t) \quad (\text{A.49})$$

$$\leq \check{\mu}_t(\mathbf{x}_t) + c^+ \beta_t(\mathbf{x}_t) + \frac{LDd}{\tau_t} - \mu(\mathbf{x}_t) \quad (\text{A.50})$$

$$\leq (c^+ + c^-) \beta_t(\mathbf{x}_t) + \frac{LDd}{\tau_t}, \quad (\text{A.51})$$

where (A.47) and (A.50) are from (A.48) and hold simultaneously with probability at least $1 - \sum_{t=1}^T \delta_t(1 + \tau_t^d)$, and (A.49) is by hypothesis, as $\mathbf{x}_t = \arg \max_{\mathbf{x} \in \tilde{\mathcal{X}}_t} (\check{\mu}_t(\mathbf{x}) + c^+ \beta_t(\mathbf{x}))$. Note that the latter is true only by virtue of the fact that both $[\mathbf{x}^*]_t$ and \mathbf{x}_t belong to $\tilde{\mathcal{X}}_t$, as the optimization step of Algorithm 3.2 is restricted to $\tilde{\mathcal{X}}_t$.

Finally, we can bound the regret. With probability at least $1 - \delta$:

$$\begin{aligned} \text{Regret}(T) &= \Delta_0 + \sum_{t=1}^T \Delta_t \\ &\leq \Delta_0 + (c^+ + c^-) \sum_{t=1}^T \beta_t(\mathbf{x}_t) + LDd \sum_{t=1}^T \frac{1}{\tau_t} \end{aligned} \quad (\text{A.52})$$

$$\leq \Delta_0 + (c^+ + c^-) \sum_{t=1}^T \beta_t(\mathbf{x}_t) + \frac{\kappa}{\kappa - 1} LDT^{(1-\frac{1}{\kappa})} d \quad (\text{A.53})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{\log \frac{1}{\delta_t}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\kappa}{\kappa - 1} LDT^{(1-\frac{1}{\kappa})} d \quad (\text{A.54})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{2 \log t + \log \left(1 + \left\lceil t^{\frac{1}{\kappa}} \right\rceil^d \right) + \log \frac{\pi^2}{6\delta}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\kappa}{\kappa - 1} LDT^{(1-\frac{1}{\kappa})} d \quad (\text{A.55})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{2 \log t + d \log \left(t^{\frac{1}{\kappa}} + 1 \right) + \log \frac{\pi^2}{3\delta}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\kappa}{\kappa - 1} LDT^{(1-\frac{1}{\kappa})} d \quad (\text{A.56})$$

$$\leq \Delta_0 + (c^+ + c^-) v_\epsilon^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T \left(\frac{\left(2 + \frac{d}{\kappa} \right) \log t + d \log 2 + \log \frac{\pi^2}{3\delta}}{t} \right)^{\frac{\epsilon}{1+\epsilon}} + \frac{\kappa}{\kappa - 1} LDT^{(1-\frac{1}{\kappa})} d \quad (\text{A.57})$$

$$\begin{aligned} &\leq \Delta_0 + (c^+ + c^-) \left[v_\epsilon \left(\left(2 + \frac{d}{\kappa} \right) \log T + d \log 2 + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} \sum_{t=1}^T t^{-\frac{\epsilon}{1+\epsilon}} + \frac{\kappa}{\kappa - 1} LDT^{(1-\frac{1}{\kappa})} \\ &\leq \Delta_0 + (c^+ + c^-) \left[v_\epsilon \left(\left(2 + \frac{d}{\kappa} \right) \log T + d \log 2 + \log \frac{\pi^2}{3\delta} \right) \right]^{\frac{\epsilon}{1+\epsilon}} (1 + \epsilon) T^{\frac{1}{1+\epsilon}} + \frac{\kappa}{\kappa - 1} LDT^{(1-\frac{1}{\kappa})} \end{aligned} \quad (\text{A.58})$$

where (A.52) is from (A.51) and holds with probability at least $1 - \delta$ with the proposed δ_t and τ_t , (A.53) is from the proposed τ_t and (A.26) with $\alpha = 1/\kappa$, (A.54) is from Assumption 3.4.1, (A.55) is from the proposed δ_t , (A.56) and (A.57) are from the fact $\log(x + 1) \leq \log(2x)$ for $x \geq 1$, and (A.57) is from (A.26) with $\alpha = \frac{\epsilon}{1+\epsilon}$. The proof is completed by renaming $C_1 \leftarrow (1 + \epsilon)(c^+ + c^-) \|f\|_\infty = (1 + \epsilon)(2\sqrt{2} + \frac{5}{3}) \|f\|_\infty$ and $C_2 \leftarrow \frac{\kappa}{\kappa - 1} LD$. \square

Lemma A.0.1. Let $\Psi = \sum_{l=1}^L \zeta_l P_l$ and $\Phi = \sum_{k=1}^K \beta_k Q_k$, with $\zeta_l \in [0, 1]$, $\sum_{l=1}^L \zeta_l = 1$, $\beta_k \in [0, 1]$ and $\sum_{k=1}^K \beta_k = 1$, be two finite mixtures of the probability measures $\{P_l\}_{l=1}^L$ and $\{Q_k\}_{k=1}^K$ respectively. Let $\{\psi_{ij}\}_{i=1,2,\dots,L}^{j=1,2,\dots,K}$ and $\{\phi_{ij}\}_{i=1,2,\dots,L}^{j=1,2,\dots,K}$

be two sets of variational parameters s.t. $\phi_{ij} \geq 0$, $\psi_{ij} \geq 0$, $\sum_{k=1}^K \phi_{ij} = \zeta_l$ and $\sum_{l=1}^L \psi_{ij} = \beta_k$. Then, for any $\alpha \geq 1$, it holds that:

$$d_\alpha(\Psi\|\Phi)^{\alpha-1} \leq \sum_{l=1}^L \sum_{k=1}^K \phi_{lk}^\alpha \psi_{lk}^{1-\alpha} d_\alpha(P_l\|Q_k)^{\alpha-1}.$$

Proof. The proof follows the idea of the variational bound for the KL-divergence proposed in [52]. Using the variational parameters we can express the two mixtures as:

$$\begin{aligned} \Psi &= \sum_{l=1}^L \sum_{k=1}^K \phi_{lk} P_l, \\ \Phi &= \sum_{l=1}^L \sum_{k=1}^K \psi_{lk} Q_k. \end{aligned}$$

We use the convexity of the d_α and we apply Jensen inequality:

$$\begin{aligned} d_\alpha(\Psi\|\Phi)^{\alpha-1} &= \int \left(\frac{\Psi}{\Phi} \right)^\alpha d\Phi \\ &= \int \left(\sum_{l=1}^L \sum_{k=1}^K \frac{\phi_{lk} P_l}{\psi_{lk} Q_k} \frac{\psi_{lk} Q_k}{\Phi} \right)^\alpha d\Phi \\ &\leq \int \sum_{l=1}^L \sum_{k=1}^K \frac{\psi_{lk} Q_k}{\Phi} \left(\frac{\phi_{lk} P_l}{\psi_{lk} Q_k} \right)^\alpha d\Phi \quad (\text{A.59}) \\ &= \sum_{i=1}^n \sum_{j=1}^m \phi_{lk}^\alpha \psi_{lk}^{1-\alpha} \int \left(\frac{P_l}{Q_k} \right)^\alpha dQ_k \\ &= \sum_{i=1}^n \sum_{j=1}^m \phi_{lk}^\alpha \psi_{lk}^{1-\alpha} d_\alpha(P_l\|Q_k)^{\alpha-1}, \end{aligned}$$

where (A.59) is obtained by Jensen inequality observing that $\frac{\psi_{lk} Q_k}{\Phi}$ is a distribution over $\{1, \dots, L\} \times \{1, \dots, K\}$. \square

We now consider the case in which f has just one mixture component, i.e., $n = 1$. In this case, we have that $\sum_{i=1}^n \psi_{ij} = \psi_j = b_j$, therefore the result reduces to:

$$d_\alpha(f\|g)^{\alpha-1} \leq \sum_{j=1}^m \phi_j^\alpha b_j^{1-\alpha} d_\alpha(f\|g_j)^{\alpha-1}. \quad (\text{A.60})$$

We can now minimize the bound over the ϕ_j , subject to $\sum_{j=1}^m \phi_j = 1$, we get the following result.

Theorem 4.1.1. *Let P be a probability measure and $\Phi = \sum_{k=1}^K \beta_k Q_k$, with $\beta_k \in [0, 1]$ and $\sum_{k=1}^K \beta_k = 1$, be a finite mixture of the probability measures*

$\{Q_k\}_{k=1}^K$. Then, for any $\alpha \geq 1$, the exponentiated α -Rényi divergence can be bounded as:

$$d_\alpha(P\|\Phi) \leq \frac{1}{\sum_{k=1}^K \frac{\beta_k}{d_\alpha(P\|Q_k)}}. \quad (4.3)$$

Proof. We now consider the case in which Ψ has just one mixture component, i.e., $L = 1$ and we abbreviate $\Psi = P$. In this case, we have that $\sum_{l=1}^L \psi_{kl} = \psi_k = \beta_k$, therefore the result reduces to:

$$d_\alpha(P\|\Phi)^{\alpha-1} \leq \sum_{k=1}^K \phi_k^\alpha \beta_k^{1-\alpha} d_\alpha(P\|Q_k)^{\alpha-1}. \quad (A.61)$$

We can now minimize the bound over the ϕ_k , subject to $\sum_{k=1}^K \phi_k = 1$. We use the Lagrange multipliers.

$$\mathcal{L}(\{\phi_k\}_{k=1,2,\dots,K}, \lambda) = \sum_{k=1}^K \phi_k^\alpha \beta_k^{1-\alpha} d_\alpha(P\|Q_k)^{\alpha-1} - \lambda \left(\sum_{k=1}^K \phi_k - 1 \right)$$

We take the partial derivatives w.r.t. the ϕ_k and the Lagrange multiplier λ .

$$\frac{\partial \mathcal{L}}{\partial \phi_k} = \alpha \phi_k^{\alpha-1} \beta_k^{1-\alpha} d_\alpha(P\|Q_k)^{\alpha-1} - \lambda = 0 \implies \phi_k = \frac{\lambda^{\frac{1}{\alpha-1}} \beta_k}{\alpha^{\frac{1}{\alpha-1}} d_\alpha(P\|Q_k)}.$$

We now replace the expression of ϕ_k into the constraint.

$$\sum_{j=1}^K \phi_j = \frac{\lambda^{\frac{1}{\alpha-1}}}{\alpha^{\frac{1}{\alpha-1}}} \sum_{k=1}^K \frac{\beta_k}{d_\alpha(P\|Q_k)} = 1 \implies \lambda = \frac{\alpha}{\left(\sum_{k=1}^K \frac{\beta_k}{d_\alpha(P\|Q_k)} \right)^{\alpha-1}}.$$

And finally we get the expression for ϕ_k :

$$\phi_k = \frac{\frac{\beta_k}{d_\alpha(P\|Q_k)}}{\sum_{h=1}^K \frac{\beta_h}{d_\alpha(P\|Q_h)}}. \quad (A.62)$$

We can now compute the bound value:

$$\begin{aligned} \sum_{k=1}^K \phi_k^\alpha \beta_k^{1-\alpha} d_\alpha(P\|Q_k)^{\alpha-1} &= \sum_{k=1}^K \frac{\frac{\beta_k^\alpha}{d_\alpha(P\|Q_k)^\alpha}}{\left(\sum_{h=1}^K \frac{\beta_h}{d_\alpha(P\|Q_h)} \right)^\alpha} \beta_k^{1-\alpha} d_\alpha(P\|Q_k)^{\alpha-1} \\ &= \frac{\sum_{k=1}^K \frac{\beta_k}{d_\alpha(P\|Q_k)}}{\left(\sum_{h=1}^K \frac{\beta_h}{d_\alpha(P\|Q_h)} \right)^\alpha} \\ &= \frac{1}{\left(\sum_{k=1}^K \frac{\beta_k}{d_\alpha(P\|Q_k)} \right)^{\alpha-1}}. \end{aligned}$$

As a consequence the bound becomes:

$$d_\alpha(P\|\Phi)^{\alpha-1} \leq \frac{1}{\left(\sum_{k=1}^K \frac{\beta_k}{d_\alpha(P\|Q_k)} \right)^{\alpha-1}} \implies d_\alpha(P\|\Phi) \leq \frac{1}{\sum_{k=1}^K \frac{\beta_k}{d_\alpha(P\|Q_k)}},$$

which is the weighted harmonic mean of the exponentiated divergences. \square

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