ARLO: A Framework for Automated Reinforcement Learning

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Abstract

Automated Reinforcement Learning (AutoRL) is a relatively new area of research that is gaining increasing attention. The objective of AutoRL consists in easing the employment of Reinforcement Learning (RL) techniques for the broader public by alleviating some of its main challenges, including data collection, algorithm selection, and hyper-parameter tuning. In this work, we propose a general and flexible framework, namely ARLO: Automated Reinforcement Learning Optimizer, to construct automated pipelines for AutoRL. Based on this, we propose a pipeline for offline and one for online RL, discussing the components, interaction, and highlighting the difference between the two settings. Furthermore, we provide a Python implementation of such pipelines, released as an open-source library. Our implementation has been tested on an illustrative LQG domain and on classic MuJoCo environments, showing the ability to reach competitive performances requiring limited human intervention. We also showcase the full pipeline on a realistic dam environment, automatically performing the feature selection and the model generation tasks.

***K*eywords** Automated Reinforcement Learning · AutoRL · AutoML

1 Introduction

Reinforcement Learning (RL, Sutton and Barto, 2018) has recently achieved successful results in solving several complex control problems, including autonomous driving (Wang et al., 2018), robot manipulators (Nguyen and La, 2019), and finance (Zhang et al., 2020). These outstanding achievements are rooted in the employment of powerful training algorithms combined with complex model representations, such as deep neural networks (Arulkumaran et al., 2017). Unfortunately, empirical experience suggests that this class of approaches heavily depends on fine-tuning, where an inaccurate choice of the hyper-parameters makes the difference between learning the optimal policy and not learning at all (Buşoniu et al., 2018). This represents an indubitable limitation, making this powerful tool not immediately usable by non-expert users. While this scenario is common even in general Machine Learning (ML, Bishop and Nasrabadi, 2006), the inherent complexity of RL, due to the sequential nature of the problem, exacerbates this issue even more.

The research effort towards the democratization of ML has reached a mature level of development for supervised learning. Indeed, several Automated Machine Learning (AutoML) frameworks and corresponding libraries have been developed and tested, such as the ones proposed by Feurer et al. (2015, 2020); LeDell and Poirier (2020); Olson et al. (2016). AutoML is intended to automate the whole ML pipeline, starting from the preliminary operations on the data, ending with the trained and evaluated final model. This way, the complete ML process can be regarded, by the non-expert user, as a black-box, abstracting from the unnecessary details and favoring the adoption of ML as a production tool. For a detailed review of the currently available AutoML frameworks, we refer the reader to the recent survey by He et al. (2021). Conversely, RL is currently far from being a tool usable by a non-expert user since a complete and reliable Automated Reinforcement Learning (AutoRL) pipeline is currently missing. This automation gap between

RL and supervised learning is even more severe from a theoretical perspective since, to the best of our knowledge, a general and flexible notion of AutoRL pipeline has not been formalized yet.

Recently, a surge of scientific works in the RL field (Parker-Holder et al., 2022; Afshar et al., 2022) attempted to tackle either specific stages of the RL pipeline *individually* (e.g., feature construction, policy generation), or focus on specific application scenarios. While providing a vast analysis of the available approaches for each single stage, they review the state-of-the-art to solve single tasks individually and do not propose a full pipeline and do not study the peculiarities characterizing the *interaction* between such stages. On the other hand, a naïve adaptation of the existing automated pipelines designed for AutoML to the RL setting is not a viable approach since they fail to capture the unique characteristics of RL related to the presence of an interacting environment and the sequential nature of the learning problem.

Contributions In this paper, we make a step towards the formalization of an AutoRL framework. The contributions of this work can be synthesized as follows.

- We propose a general and flexible formalization of a *pipeline* for AutoRL. Grounding on such a definition, we instantiate it for two different scenarios: *offline* and *online* RL.[1] The former assumes that the RL process is carried out based on a fixed *batch* of data. The latter takes into account the availability of an interactive environment.
- We describe the individual *stages* of the two pipelines and their respective characteristics, highlighting the *interactions* between them and focusing on their inputs and outputs. Furthermore, we discuss the corresponding *units*, i.e., possible implementations of stages, and introduce a general approach to select the best-tuned unit in a finite set.
- We provide an implementation of the framework in an open-source Python library, called ARLO.[2] The library contains the implementation of all the stages, the two RL pipelines, and the needed tools to run, optimize, and evaluate the pipelines.
- Finally, we test the implementation on an illustrative LQG and a MuJoCo environment, showing the ability to reach optimal performances without requiring any manual adjustment by humans. At last, we provide an experiment on a realistic dam environment with a pipeline performing the data generation, feature selection, policy generation, and policy evaluation stages.

Given the wide variety of RL problems and solutions, we restrict our formalization to the case of *stationary* and *fully observable* environments. We leave the extension to more complex settings (e.g., multi-objective, multi-agent, lifelong) as a future work.

Limitations and Broader Impact Statement The goal of AutoRL is to bring RL closer to the non-expert user. This represents a source of opportunities and risks. On the one hand, making RL usable to a wide audience contributes to the *democratization* of the field, overcoming the need for specific education and opening it to the large public. On the other hand, such an abstract approach tends to compromise the transparency of the learning process and traceability of the resulting model. Shadowing the underlying principles, AutoRL might pose the risk of misuse of RL approaches, leading to results not in line with expectations. Furthermore, AutoRL, even more than RL, requires huge amounts of data and computation that might represent a limit of the framework.

Outline The paper is structured as follows. In Section 2, we present the fundamental notions of Markov Decision Processes and the basics of RL. In Section 3, we introduce a general notion of pipeline, stage, and unit. In Section 4, we present the online and offline pipelines for RL. In Section 5, we describe the details of the components included in the two pipelines. In Section 6, we report the results of the tests performed on standard benchmarks and on a realistic environment. In Section 7, we highlight the conclusions of our works and we propose future research lines.

2 Preliminaries

A Markov Decision Process (MDP, Puterman, 2014) is defined as a tuple $\mathcal{M} = (\mathcal{S}, \mathcal{A}, P, R, \gamma, \mu_0)$, where $\mathcal{S}$ is the set of states, $\mathcal{A}$ is the set of actions, $P(s'|s,a)$ is the state transition model, specifying the probability to land in state s' starting from state s and performing action a, $R(s,a)$ is the reward function, defining the expected reward when the agent is in state s and performs action a, $\gamma \in [0,1]$ is the discount factor, and $\mu_0(s)$ is the initial state distribution. The agent's behavior is defined in terms of a policy $\pi(a|s)$ defining the probability of performing action a in state s.

[1] The reader might be tempted to address the offline RL setting with AutoML, given the fixed available dataset and, thus, the similarity with supervised learning. We stress that this choice is inappropriate as the peculiarities of RL are still crucial, especially the sequential properties of the problem.

[2] The library is available at `https://github.com/arlo-lib/ARLO`.

Interaction Protocol The initial state is sampled from the initial-state distribution $s_0 \sim \mu_0$, the agent selects an action based on its policy $a_0 \sim \pi(\cdot|s)$, the environment provides the agent with the reward $R(s_0, a_0)$, and the state evolves according to the transition model $s_1 \sim P(\cdot|s_0, a_0)$. The process is repeated for T steps, where $T \in \mathbb{N} \cup \{+\infty\}$ is the (possibly infinite) horizon.

Objective The goal of RL consists in learning an *optimal* policy $\pi(a|s)$, i.e., a policy maximizing the expected discounted sum of the rewards, a.k.a. the *expected return* (Sutton and Barto, 2018):

$$J(\pi) := \mathbb{E}^{\pi}\left[\sum_{t=0}^{T-1} \gamma^t R(s_t, a_t)\right], \tag{1}$$

where the expectation $\mathbb{E}^{\pi}[\cdot]$ is computed w.r.t. the randomness of environment and policy.

Environments and Datasets We introduce the notion of *environment* and *dataset*. Formally, an environment $\mathcal{E}$ is a device to interact with the underlying MDP, that, given a state s_t and an action a_t, it provides the next state $s'_t \sim P(\cdot|s_t, a_t)$ and the reward $r_t = R(s_t, a_t)$. An environment is a *generative model* if it allows to freely choose the state s_t at each step, or a *forward model* if, instead, we can perform steps in the MDP ($s_{t+1} = s'_t$) or start again sampling s_t from the initial-state distribution μ_0. A dataset $\mathcal{D} := \{\tau_i\}_{i=1}^n$ is a set of trajectories τ_i, where each *trajectory* is a sequence $\tau_i = (s_i^0, a_i^0, r_i^1, \dots, s_i^{T_i-1}, a_i^{T_i-1}, r_i^{T_i}, s_i^{T_i})$ and T_i is the length of the trajectory.

Online vs. Offline RL We distinguish between two main groups of RL algorithms: *online* and *offline* RL. The online RL algorithms (Sutton and Barto, 2018) aim at learning a policy π by directly interacting with an environment $\mathcal{E}$. Typically they employ the last available policy to collect data and leverage the experience to improve it. Conversely, the offline RL paradigm (Levine et al., 2020) consists in carrying out the policy learning on a dataset $\mathcal{D}$ previously collected.[3] The ability to learn a (near-)optimal policy heavily depends on the exploration properties of the dataset $\mathcal{D}$.

Regarding offline RL, several works covered its peculiarities. In Levine et al. (2020) the authors survey the field of offline RL, presenting open problems, unique challenges and limitations. In Paine et al. (2020) the authors focused on the evaluation problem present in offline RL, namely on the evaluation of a learnt policy without resorting to an environment. Furthermore, this work showcases how offline RL algorithms are not robust with respect to hyper-parameters tuning.

3 Framework

In this section, we present the abstract formalization of the proposed AutoRL pipeline, detailing the notions of *pipeline*, *stage*, and *unit*.

Stages and Pipelines A stage ψ represents a single component of the pipeline with a specific *purpose*. For instance, the portion of the pipeline in charge of performing feature engineering is regarded as a stage. A stage ψ interacts with the other stages of the pipeline by means of an *interface*, defining its inputs and outputs. We denote a stage's inputs with $\mathrm{In}(\psi)$ and its outputs with $\mathrm{Out}(\psi)$. A pipeline is a sequence of $m \in \mathbb{N}$ stages $\Psi = (\psi_1, \dots, \psi_m)$. The possibility of staking specific stages in sequence depends, in general, on problem-dependent constraints.

Units A unit constitutes the actual *implementation* of the stages corresponding to algorithms that are in charge of generating the output required by the corresponding stage.[4] We define three relevant types of units: *fixed*, *tunable*, and *automatic*.

Fixed Unit A fixed unit (Figure 1a) corresponds to an algorithm $\psi = \mathfrak{A}(h)$, where $\mathfrak{A}(h)$ denotes algorithm $\mathfrak{A}$ that generates the stage output, instanced with hyper-parameters $h \in \mathcal{H}$ selected from an hyper-parameter set $\mathcal{H}$.

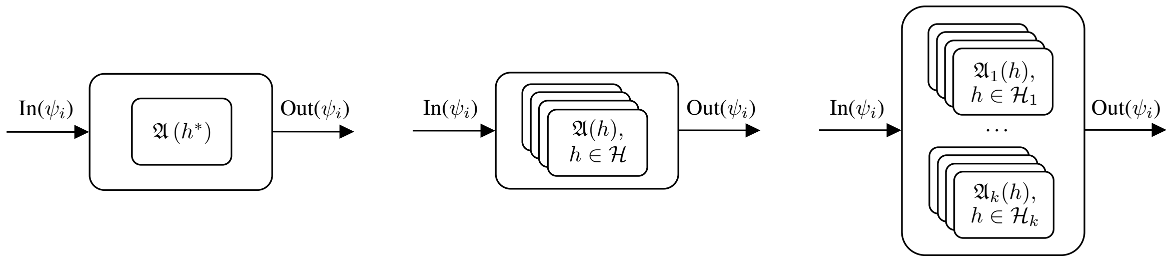
Tunable Unit A tunable unit (Figure 1b) is described by a tuple $\psi = (\mathfrak{A}, \mathcal{H}, \mathfrak{T}, \ell)$ where $\mathfrak{A}(\cdot)$ is an algorithm, $\mathcal{H}$ is a *hyper-parameters set*, $\mathfrak{T}$ is a *tuner* (e.g., genetic algorithm, particle swarm, Bayesian optimizer), and $\ell(\mathfrak{A}, h) \in \mathbb{R}$ is a tuning *performance index* mapping an algorithm $\mathfrak{A}(\cdot)$ and hyper-parameters $h \in \mathcal{H}$ pair to a real number. The *tuning optimization problem* can be formulated as finding the hyper-parameters $h^* \in \mathcal{H}$ maximizing the performance index ℓ. Formally:

$$h^* \in \arg\max_{h \in \mathcal{H}} \ell(\mathfrak{A}, h).$$

This optimization is addressed by the tuner $\mathfrak{T}$. When the stage corresponding to the tunable unit is executed, it reduces to the fixed unit $\mathfrak{A}(h^*)$, and, subsequently, it generates the block outputs.

[3] Even in this case, we may have an environment $\mathcal{E}$ to test the performance of the learned policy. Commonly, it is a less costly version, e.g., in terms of computational or real costs, of the environment where the final policy will be applied.

[4] From a software engineering perspective, a stage is an abstract class, while a unit a concrete class.



(a) Fixed Unit. (b) Tunable Unit. (c) Automatic Unit.

Figure 1: The three types of units.

Automatic Unit An *automatic unit* (Figure 1c) is a set of tunable units paired with a performance index, i.e., $\psi = (\{\psi_j\}_{j=1}^k, \ell)$, where $\psi_j = (\mathfrak{A}_j, \mathcal{H}_j, \mathfrak{T}_j, \ell_j)$, for $j \in \{1, \dots, k\}$, and $\ell(\mathfrak{A}, h) \in \mathbb{R}$ is a performance index for algorithm $\mathfrak{A}$ with hyper-parameters h. The goal of an automatic unit consists in selecting the best tuned algorithm among the available ones, by ranking them based on the additional performance index ℓ. We define the *automatic optimization problem* as follows:

$$j^* \in \operatorname*{arg\,max}_{j \in \{1,\dots,k\}} \ell(\mathfrak{A}_j, h_j^*), \qquad \text{where} \qquad h_j^* \in \operatorname*{arg\,max}_{h \in \mathcal{H}_j} \ell_j(\mathfrak{A}_j, h), \quad j \in \{1, \dots, k\}.$$

When the stage corresponding to the automatic unit is executed, it reduces the automatic unit a fixed one $\mathfrak{A}_{j^*}(h_{j^*}^*)$, and, subsequently, it generates the corresponding output.

The problem of jointly finding the best algorithm and its related hyper-parameter configuration is also referred in the AutoML community as CASH (Combined Algorithm Selection and Hyper-parameter Optimization Problem, Thornton et al., 2013).

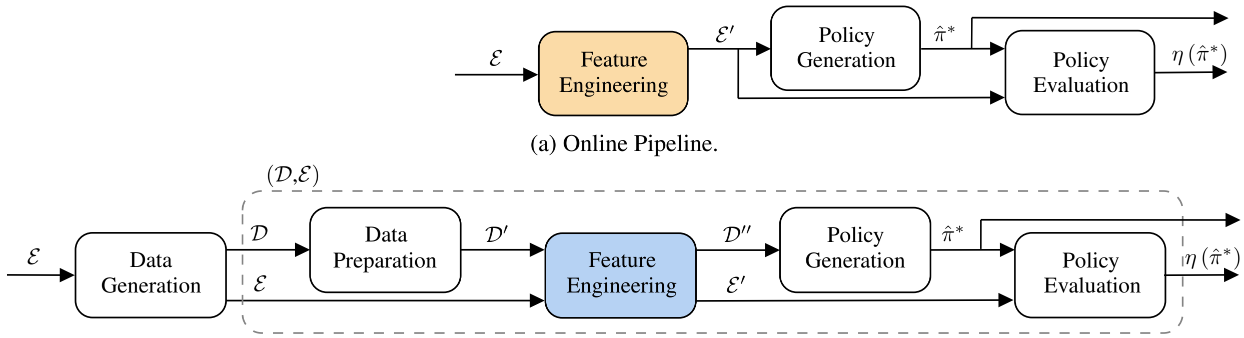
Intuitively, a fixed unit is a human hand-crafted unit in which an algorithm is selected and the related hyper-parameters are specified. No automatic operations nor evaluation are performed here. In a tunable unit, the algorithm is specified but the task to find the best hyper-parameter configuration is demanded to the pipeline. In an automatic unit, both the choice of the best algorithm and the best hyper-parameter configuration is demanded to the pipeline.

4 AutoRL Pipelines

In this section, we present the main methodological contribution of the paper, discussing the two AutoRL pipelines: *online* and *offline*. We focus on how to build these pipelines describing the stages' interactions. The detailed description of each individual stage is reported in Section 5. A graphical representation of the pipelines is provided in Figure 2.

Online Pipeline The *Online AutoRL Pipeline* (Figure 2a) takes as input an environment $\mathcal{E}$ that is fed to the `Feature Engineering` stage, which modifies its state/action representations and the reward to facilitate the learning performed in the next stages. It outputs a transformed environment $\mathcal{E}'$, based on the features created in this stage. Subsequently, the environment $\mathcal{E}'$ is used to learn an estimate $\hat{\pi}^*$ of the optimal policy through the `Policy Generation`. Finally, the `Policy Evaluation` phase provides an estimate of the performance $\eta(\hat{\pi}^*)$, based on a performance index η.

Offline Pipeline In the *Offline AutoRL Pipeline* (Figure 2b), differently from the online one, two additional preliminary stages are included: `Data Generation` and `Data Preparation`. If an environment $\mathcal{E}$ is provided as input, the `Data Generation` stage creates a dataset $\mathcal{D}$. This stage is omitted if a dataset $\mathcal{D}$ is already available, e.g., in the case the dataset $\mathcal{D}$ comes from a real process. In such a case, the environment $\mathcal{E}$ is employed for the evaluation of the policy performance only. The `Data Preparation` stage modifies the dataset $\mathcal{D}$, by applying corrections over the individual instances (i.e., the rows of the dataset) obtaining $\mathcal{D}'$. Then, the environment $\mathcal{E}$ and dataset $\mathcal{D}'$ pass through the `Feature Engineering` stage, which, similarly to its online counterpart, generates a dataset $\mathcal{D}''$ and an environment $\mathcal{E}'$ with transformed states, actions, and reward. After that, the dataset $\mathcal{D}''$ is used for learning an estimate of the optimal policy $\hat{\pi}^*$ through the `Policy Generation` stage. Differently from the online one, this stage uses the dataset $\mathcal{D}''$, while the environment $\mathcal{E}'$ is employed for estimating $\eta(\hat{\pi}^*)$ in the `Policy Evaluation` stage.



(a) Online Pipeline.

(b) Offline Pipeline.

Figure 2: The Online (a) and Offline (b) AutoRL Pipelines.

5 Stages and Units

We now provide examples of units for each of the stages, highlighting the differences between the online and offline pipelines. For each stage, we define its goal, performance index for tunable or automatic units, and implementation selected from the state-of-the-art methodologies.

5.1 Data Generation

The `Data Generation` stage takes as input an environment $\mathcal{E}$ and returns the unaltered environment $\mathcal{E}$ and a dataset $\mathcal{D}$ generated by interacting with the environment. The goal of this stage is to create a dataset that is retrieved by exploring the state space as much as possible. Based on the type of environment, i.e., generative or forward model, the resulting dataset is made of transitions or trajectories.

In principle, this stage should output a dataset as "informative" as possible, i.e., that represents exhaustively the corresponding environment. As performance index for evaluating the quality of a `Data Generation` unit, we adopt the *entropy* of the state-action visitation distribution $d_\pi(s,a)$ generated by the policy $\pi(a|s)$, that is proportional to:

$$-\int_{s\in\mathcal{S}}\int_{a\in\mathcal{A}} d_\pi(s,a)\log d_\pi(s,a)da\, ds.$$ [5]

A straightforward implementation of `Data Generation` consists in collecting data with the random uniform policy. However, this approach is not guaranteed to explore the state space effectively (Mutti et al., 2021; Endrawis et al., 2021). In the pipeline, we consider the state-of-the-art solutions proposed by Pathak et al. (2019), and Mutti et al. (2021). The former employs Proximal Policy Optimization (PPO, Schulman et al., 2017) using the estimated variance of the MDP dynamics as reward, as a proxy for the entropy. Instead, the latter provides a novel policy search algorithm maximizing a K-nearest neighbours-based estimate of the state distribution entropy.

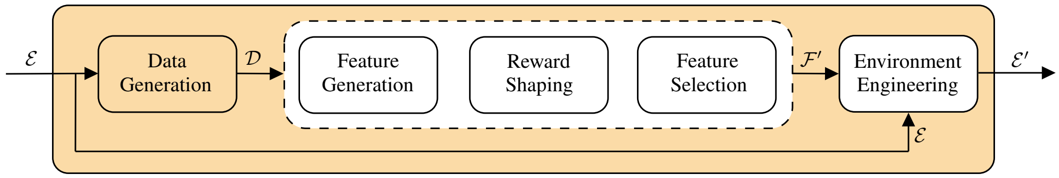
5.2 Data Preparation

This phase uses a dataset $\mathcal{D}$, coming either from a real-world environment or generated in the `Data Generation` stage, and returns a dataset $\mathcal{D}'$ with the same state-action features and reward, but with a possibly different number of entries. The goal of this phase is to optimize an existing dataset in order to be processed better from in subsequent stages. `Data Preparation` includes data augmentation, data imputation, and data scaling, and can embed further domain-specific sub-stages (e.g., for images, audio data), and/or consistency checks (e.g., filling missing values).

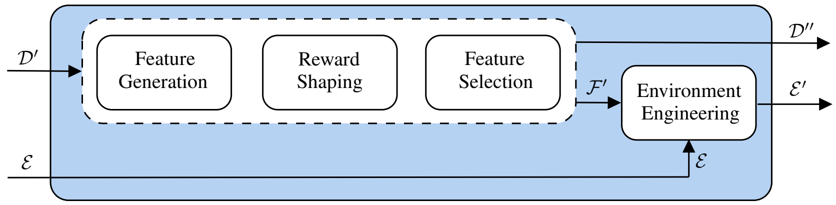
No single automatic unit is deemed adoptable due to the difficulty of defining a general enough performance index for this stage. However, domain-specific performance indexes are available, e.g., for the data imputation sub-stages, we may rely on the indexes defined by Jadhav et al. (2019).

Possible implementations of this stage include the techniques for classical ML preprocessing, such as imputation from a dataset of trajectories via KNN imputation or Bayesian Multiple Imputation (Lizotte et al., 2008). Moreover, for pixel-based observations (e.g., the Gym Atari environments) data augmentation techniques, e.g., cropping, reflection, scaling, were employed in Ye et al. (2020). Other approaches viable for feature-based representations are presented in Laskin et al. (2020), where experiments on the OpenAI Procgen Benchmark and on the MuJoCo environments.

[5] In this stage, we rely on the Particle Based Entropy estimation developed by Singh et al. (2003).



(a) Feature Engineering stage in Online Pipeline.



(b) Feature Engineering stage in Offline Pipeline.

Figure 3: The offline and online `Feature Engineering` stages.

5.3 Feature Engineering

The `Feature Engineering` stage displays significant differences between online and offline pipelines (Figure 3). Offline pipelines (Figure 3b) take as input an environment $\mathcal{E}$ and a dataset $\mathcal{D}'$ and return a feature-adjusted environment $\mathcal{E}'$ and dataset $\mathcal{D}''$. Conversely, online pipelines (Figure 3a) take as input an environment $\mathcal{E}$ and return a feature-adjusted environment $\mathcal{E}'$. In both cases, this stage requires an internal dataset for feature engineering that, for the online case, has to be generated.

The core task of this stage is to select and generate a set of features that properly model the state-action space of the problem and perform reward shaping actions to facilitate the following learning phase. `Feature Engineering` stage includes one or more of the following *sub-stages*:

- `Feature Generation`, in charge of creating new features. This sub-stage makes use of techniques such as radial basis functions, tile coding, or coarse coding (Sutton and Barto, 2018).
- `Feature Selection`, aimed at selecting a meaningful subset of features, either to reduce the computation requirements or to regularize the following policy learning phase. Viable options are Mutual Information-based selection (Beraha et al., 2019), correlation-based filtering methods, and tree-based variable selection (Castelletti et al., 2011).
- `Reward Shaping`, performing specific transformations on the reward function, possibly preserving the optimal policy, to speed up the convergence of an RL algorithm (Ng et al., 1999). For instance, in presence of sparse reward functions, reward shaping can be regarded as a form of *curriculum learning* (Portelas et al., 2020).

These sub-stages return a transformation that is applied to the environment through the `Environment Engineering` stage. In the offline case, the same transformation is applied to the dataset, while for the online case the internal dataset is disregarded.

We consider as a performance index for the complete feature engineering stage the mutual information between the current state-action pair (s, a) features and the next-state reward (s', r) features (Kraskov et al., 2004; Gao et al., 2017) regularized, e.g., by the number of selected features.[6]

5.4 Policy Generation

The `Policy Generation` stage is in charge of the training phase of the RL learning algorithm. More specifically, it takes as input an environment $\mathcal{E}'$ or a dataset $\mathcal{D}''$, in the online and offline RL pipelines, respectively, to output an estimate $\hat{\pi}^*$ of the optimal policy.

Among the most common choices of performance indexes for this stage, we mention the *expected return*, i.e., the expected discounted sum of the rewards, the *average reward*, i.e., the long-term expected average reward, and the *total reward* i.e., expected cumulative sum of the rewards (in the case the environment is episodic, Puterman, 2014).

[6]For instance, one may use the ratio between the mutual information and the number of selected features.

For specific applications, e.g., risk-averse setting, one may adopt the mean-variance, mean-volatility, and CVaR (Pratt, 1978; Bisi et al., 2021).

Many works deal with hyper-parameter optimization for RL algorithms. In Franke et al. (2021) a framework based on Population Based Training (PBT, Jaderberg et al., 2017) is proposed to tune off-policy RL algorithms. In Parker-Holder et al. (2021) a new time-varying bandit algorithm was presented for tuning RL algorithms. Hyper-parameter tuning is a widely researched topic and the techniques developed by ML algorithms can be used for RL algorithms as well. Nevertheless, the sample inefficiency of tuning techniques is a common problem, not unique to RL. Another issue is the sensitivity to hyper-parameters configurations, which increases the difficulty of benchmarking tuning algorithms due to the difficulty of obtaining reproducible results. Further methods were proposed by Zhang et al. (2021); Lee et al. (2021); Team et al. (2021); Saphal et al. (2021); Falkner et al. (2018).

The specific implementation of the `Policy Generation` stage depends on the selected RL algorithm. For offline pipelines, we mention, among the others, Least Squares Policy Iteration (LSPI, Lagoudakis and Parr, 2003), Fitted Q-Iteration (FQI, Ernst et al., 2005). For online pipelines, a large surge of RL algorithms have been developed in the recent years. We mention, among the most popular ones, Deep Q-Networks (DQN, Schaul et al., 2016), Deep Deterministic Policy Gradient (DDPG, Lillicrap et al., 2016), Trust Region Policy Optimization (TRPO, Schulman et al., 2015), Soft Actor Critic (SAC, Haarnoja et al., 2018), and Proximal Policy Optimization (PPO, Schulman et al., 2017).

5.5 Policy Evaluation

The `Policy Evaluation` stage takes as input the policy $\hat{\pi}^*$ produced by the `Policy Generation` phase and an environment $\mathcal{E}'$, and produces as output an estimation of a performance index $\eta(\hat{\pi}^*)$.

Regarding the performance index used in this stage, the options are the same we mentioned for `Policy Generation`. Notice that the performance index chosen in this stage may differ from the one of the `Policy Generation` one. For instance, it is a common practice to train RL algorithms using a discounted objective and evaluate the resulting policies using an undiscounted one (Duan et al., 2016). Notice that, due to the nature of the task, only fixed units are used in this stage.

6 Experimental Results

In this section, we use the Python implementation of ARLO on 3 RL problems. In addition to the presented stages, the library also allows to create newly defined stages, if needed, and a set of analysis tools. The implementation of the framework is available at `https://github.com/arlo-lib/ARLO`. The implemented methods are reported in Appendix A. The `Policy Generation` stages have been integrated with the MushroomRL (D'Eramo et al., 2021) library.[7] The optimization of the tunable units has been performed using a genetic algorithm as described in B. A comprehensive description of all the features available in the ARLO library, as well as details on how to integrate already developed methods for RL, are provided at `https://arlo-lib.github.io/arlo-lib`.

In Sections 6.1 and 6.2, we present the results our online pipelines whose `Policy Generation` stages contain tunable units to select the best hyper-parameters over two simulated problems. In Section 6.3, we consider an offline pipeline including tunable `Feature Engineering` and `Policy Generation` stages on a realistic dam control problem. The experimental details are reported in the supplementary material.

For the different experiments we considered different seeds. These did not only influence the RL algorithm, but were used for all the components making up the considered pipeline.

6.1 Linear Quadratic Gaussian Regulator

In this experiment, we address a Linear-Quadratic Gaussian Regulator (LQG, Dorato et al., 1994) by the state dynamics $s_{t+1} = As_t + Ba_t + \sigma$, where s_t is the state at time t, a_t is the action at time t, A is the state dynamic matrix, B is the action dynamic matrix, and σ is a Gaussian white noise. The reward function is $r_{t+1} = -s_t^T Q s_t - a_t^T R a_t$, where Q and R are the state and action cost weight matrices respectively[8]. The discount factor is equal to $\gamma = 0.9$ and the time horizon is $T = 15$.

We employ the *Soft-Actor Critic* (SAC, Haarnoja et al., 2018) algorithm. To tune its hyper-parameters, we create an online RL pipeline, using the expected return (Eq. (1)) as performance index, and a genetic algorithm (like in

[7]The ARLO library includes an easy procedure to integrate algorithms coming from other RL libraries.

[8]The details about the hyper-parameters configuration space, the tuning procedure, and the compute requirements for the LQG experiment can be found in the Appendix B.1.

Sehgal et al., 2019) as tuning algorithm. The results are obtained after 50 generations of the genetic algorithm, each using a population of 20 agents.

Table 1: Results achieved tuning SAC hyper-parameters on an LQG environment.

Method	Default	Tuned
Van Dooren (1981)	-7.2 (4.9)	
1^{st} Seed	-59.0 (24.0)	-8.6 (4.7)
2^{nd} Seed	-67.4 (16.1)	-8.2 (5.1)
3^{rd} Seed	-52.4 (12.5)	-8.7 (4.7)

Table 2: Results achieved tuning DDPG hyper-parameters on HalfCheetah-v3 environment.

Method	Default	Tuned
Islam et al. (2017)	3725.3 (512.8)	
1^{st} Seed	1157.7 (45.6)	3407.2 (952.1)
2^{nd} Seed	850.8 (78.9)	4624.6 (110.9)
3^{rd} Seed	956.2 (34.2)	3076.9 (77.9)

Results We compare the results provided by the ARLO framework with the optimal solution (Van Dooren, 1981). In Table 1, we report the estimated expected return, averaged over 100 episodes (with the standard deviation in brackets), for the default configuration and the corresponding tuned policy over three different seeds. Even if the performance of the tuned algorithms does not match the one of the optimal solution, the *default* hyper-parameter configuration of SAC is notably under-performing (≈ 5 times worse) compared to the tuned configuration (≈ 1.2 times worse). This result suggests that the proposed framework can generate solutions compatible with the optimal one without exploiting specific domain knowledge about the problem.

6.2 HalfCheetah

In the second experiment, we apply the online RL pipeline to the MuJoCo HalfCheetah-v3 environment from OpenAI Gym (Brockman et al., 2016).[9] As learning algorithm for the `Policy Generation` we employ the *Deep Deterministic Policy Gradient* (DDPG, Lillicrap et al., 2016), whose hyper-parameter tuning is known to be a challenging task (Islam et al., 2017)[10]. The hyper-parameters of DDPG have been tuned using the undiscounted cumulative reward as a performance index and, as a tuner, a genetic algorithm. We employ a discount factor $\gamma = 1$ and the time horizon to $T = 1000$.

Results In Table 2, we report the estimated total reward, averaged over 100 episodes, for the default and tuned configurations over three different seeds (the standard deviation is provided in brackets). The provided performances are in line with the literature ones (Islam et al., 2017) and show that the proposed pipeline provides an automatic way of achieving competitive performance. In Figure 4, we report the different hyper-parameters selected during the learning phase by individuals (agents) used in the genetic algorithm optimization procedure throughout the tuning procedure. These results show how some of the parameters have a strong influence on the reward obtained by the agents, i.e., the actor and critic learning rate and the steps per fit (Figures 4a, 4b, and 4c, respectively), which implies that the value of the parameter concentrates around the optimal value after a few generations of the genetic algorithm. Conversely, those which do not influence the outcome of the optimization procedure, i.e., the steps (Figure 4d), continue to explore the available range until the end of the generations.

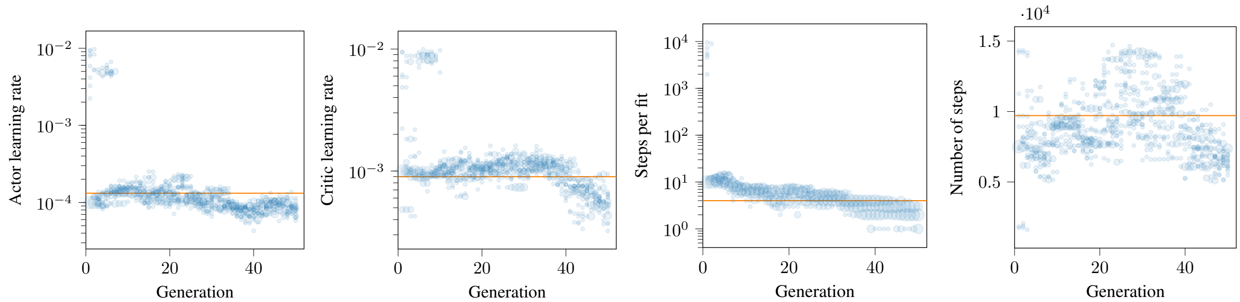
6.3 Dam

To showcase the capabilities of our framework, we propose an experiment with a more complex offline RL pipeline that includes `Data Generation`, `Feature Engineering`, `Policy Generation`, and `Policy Evaluation` stages[11]. The selected environment consists of the control of a water reservoir (dam) that models the dynamics of a real alpine

[9] `https://www.gymlibrary.ml/pages/environments/mujoco/half_cheetah`.

[10] The details about the hyper-parameters configuration space, the tuning procedure, and the compute requirements for the HalfCheetah experiment can be found in the Appendix B.2.

[11] The details about the hyper-parameters configuration space, the tuning procedure, and the compute requirements for the Dam experiment can be found in the Appendix B.3.



(a) Actor learning rate. (b) Critic learning rate. (c) Steps per fit. (d) Number of steps.

Figure 4: Values of the hyper-parameters generated by the genetic optimization procedure over the 50 generations. The orange line corresponds to the best found value.

Table 3: Results achieved tuning the hyper-parameters of a Feature Engineering stage.

Method	Discounted Reward
Baseline	-1649.85 (112.88)
Tuned Configuration	-1224.67 (124.41)

lake (Castelletti et al., 2011). The agent observes the current level of the lake and the sequence of the most recent 30 daily inflows. The actuation consists of the amount of daily water release. The goal of the agent is to trade-off between avoiding floods and fulfilling the downstream water demand. The dataset is generated using a random uniform policy. The `Feature Engineering` stage performs forward feature selection via mutual information (as presented in Beraha et al., 2019) to identify a subset of the available inflows features. The `Policy Generation` stage uses the Fitted Q-Iteration (FQI, Ernst et al., 2005) algorithm. The hyper-parameters of FQI are fixed to a hand-tuned configuration as the one presented by Tirinzoni et al. (2018). The objective of this experiment is to show in a realistic environment that tuning the hyper-parameters of a `Feature Engineering` stage is beneficial for the final performance. **Results** In Table 3, we report the estimated expected return over 10 episodes for the baseline configuration (standard deviation in brackets), in which all the features have been considered, and for the tuned configuration, in which only a subset of the features was selected automatically by the pipeline. We observe that the result achieved by the tuned agent significantly outperforms the baseline one, meaning that the feature selection techniques select only the most informative feature for the problem, with beneficial effects on the successive learning phase.

7 Conclusions and Limitations

Conclusions This paper introduced the ARLO framework for automating reinforcement learning by proposing two pipelines, one for the online setting and one for the offline setting. Moreover, we showcased the capabilities of such a framework by creating a Python library, and we tested its performance in both simulated and realistic settings. While the proposed framework in its current formulation is flexible and allows adding customized stages, the complete democratization of RL is far from being achieved. First, the procedures to optimize the different stages revealed to be computationally demanding. Thus, adding tools to predict and control the amount of computational time required by a pipeline is of paramount importance to obtaining a flexible tool. Another interesting development, going in the opposite direction of what we have just mentioned, consists in including a "whole pipeline optimization" procedure, which *jointly* optimize the entire learning process. This direction requires a preliminary development of less computationally demanding algorithms for each stage of the pipeline. Finally, we focused our attention on fully-observable, stationary, single agent, single-objective settings. Developing a more general pipeline to relax some or all the above assumptions would ease the application of RL algorithms in a more wide spectrum of real-world problems.

Limitations The goal of AutoRL is to bring RL closer to the non-expert user. This represents a source of opportunities and risks. On the one hand, making RL usable to a wide audience contributes to the *democratization* of the field, overcoming the need for specific education and opening it to the large public. On the other hand, such an abstract approach tends to compromise the transparency of the learning process and traceability of the resulting model. Shadowing the underlying principles, AutoRL might pose the risk of misuse of RL approaches, leading to results not in line with expectations. Furthermore, AutoRL, even more than RL, requires huge amounts of data and computation that might represent a limit of the framework.

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Supplementary Material for the Paper: "ARLO: A Framework for Automated Reinforcement Learning"

A Library

ARLO is a Python library implementing the framework described in this paper. It contains all the automation capabilities described in the main paper. It also provides the implementation of specific stages for each phase of the two pipelines we introduced in Section 4.

The RL algorithms present in the implementation are wrappers of those implemented in *MushroomRL* (D'Eramo et al., 2021). Moreover, we structured the library so that one has the option to implement wrappers for any other RL library, e.g., Stable Baselines, RLLib, Tensorforce.

Supported Units In Table 4, we list the currently implemented units for each stage. As mentioned before, this is a non-exhaustive list of the possible methods that can be included in the proposed framework, but only those which we used for experimental purposes. See Section 5 for some suggestions about the methods which are appropriate for an extension for each stage.

Table 4: Supported units in the current ARLO implementation.

Stage	Implementations
`Data Generation`	Random Uniform Policy
	MEPOL (Mutti et al., 2021)
`Data Preparation`	Mean Imputation
	1-NN Imputation
`Feature Engineering`	Recursive Feature Selection
	Forward Feature Selection via Mutual Information (Beraha et al., 2019)
	Nystroem Map Feature Generation
`Policy Generation`	Fitted-Q Iteration (FQI, Ernst et al., 2005)
	Double Fitted-Q Iteration (DoubleFQI, D'Eramo et al., 2017)
	Least Squares Policy Iteration (LSPI, Lagoudakis and Parr, 2003)
	Deep Q-Network (DQN, Mnih et al., 2015)
	Proximal Policy Optimization (PPO, Schulman et al., 2017)
	Deep Deterministic Policy Gradient (DDPG, Lillicrap et al., 2016)
	Soft Actor Critic (SAC, Haarnoja et al., 2018)
	GPOMDP (Baxter and Bartlett, 2001)

Used Libraries ARLO requirements, in terms of libraries, are: catboost (v1.0.3), gym (v0.19.0), joblib (v1.1.0), matplotlib (v3.5.0), mushroom_rl (v1.7.0), numpy (v1.22.0), optuna (v2.10.0), plotly (v5.4.0), scikit_learn (v1.0.2), scipy (v1.7.3), torch (v1.10.1), xgboost (v1.5.1).

B Details on the Experiments

All the experiments were run on a Linux-based server with an *AMD Ryzen* 9 $5950X$ 16-Core Processor with 128GB DDR4 RAM running *Python* 3.8.8 on *CentOS* 8.5.2111.

Hyper-parameter tuning The pseudo-code of the genetic tuner is detailed in Algorithm 1. The hyper-parameter tuning of the genetic algorithms are run for 50 generations, each one including 20 agents. Throughout each generation, *elitism* is performed, i.e., the best agent of the generation is preserved, and the new generation is created via tournament selection. More specifically, we take the best agent, out of a subset of 3 agents of the previous generation, and we

Algorithm 1 Genetic Tuner

Randomly initialise first generation
for $i \in [0, \ldots, n\_generations)$ **do**
  Fit and evaluate each agent in the generation i
  Select the best agent and add it to the new generation $i + 1$
  for $j \in [0, \ldots, n\_agents - 1)$ **do**
    Add best agent, out of a random subset of 3, to the new generation $i + 1$
  end for
  Mutate the new generation $i + 1$
end for

Table 5: Supported environments in the current ARLO implementation.

Source	Type	Environment
Gym	Classic Control	Grid World
		Mountain Car
		Cart Pole
	MuJoCo	Inverted Pendulum
		Walker2d
		HalfCheetah
		Ant
		Hopper
		Humanoid
		Swimmer
Other	Controller	LQG

repeat such an operation until 19 agents are selected (as the remaining spot is reserved for the best performing agent in the previous generation).

Each hyper-parameter is mutated with probability 0.5 and two different types of mutation can take place:

- for *categorical* hyper-parameters and for the ones having a discrete support, we sample from a uniform distribution over the possible values;
- for *numerical*, i.e., continuous domains, we sample hyper-parameters from a uniform distribution over 0.8 and 1.2 times of the current value of the hyper-parameter.

ARLO implements the Genetic Algorithm presented above as well as the hyper-parameter tuning solutions from Optuna (Akiba et al., 2019).

In all the experiments, we chose reasonable hyper-parameters configuration spaces so that they weren't neither too small, to avoid exploring a space that was too little and thus finding solutions quite far off, nor too large, to avoid increasing the total computational time (as some hyper-parameters have a great impact on the training time of the `Policy Generation` units).

Environment Whenever an environment is used for the training of a RL algorithm, a deep copy of such an environment is provided to each agent in the generation, while in the case a dataset is used for the training of a RL algorithm, we provided each agent with a bootstrapped dataset coming from the original one. The environments currently available are presented in Table 5.

Loss Function As loss function for guiding the tuning procedure we used the empirical expected return defined in Equation (1). The specific loss functions used in the different experiments for policy evaluation are detailed in the following sections.

Table 6: Hyper-parameters configuration space for the Linear Quadratic Gaussian Regulator experiment.

Hyper-parameter	Search Space
Actor Learning Rate	$\{10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}\}$
Actor Network	One layer with 16 neurons and ReLU activation
Critic Learning Rate	$\{10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}\}$
Critic Loss	MSE
Critic Optimizer	Adam
Critic Network	One layer with 16 neurons and ReLU activation
Batch Size	{8, 16, 32, 64, 128}
Initial Replay Size	{10, 100, 300, 500, 1000, 5000}
Max Replay Size	{3000, 10000, 30000, 100000}
Warmup Transitions	{50, 100, 500}
Tau	0.005
Alpha Learning Rate	$\{10^{-5}, 10^{-4}, 10^{-3}\}$
Log Std Min	-20
Log Std Max	3
N Epochs	[1, 30]
N Episodes	[1, 1600]
N Episodes Per Fit	[1, 500]

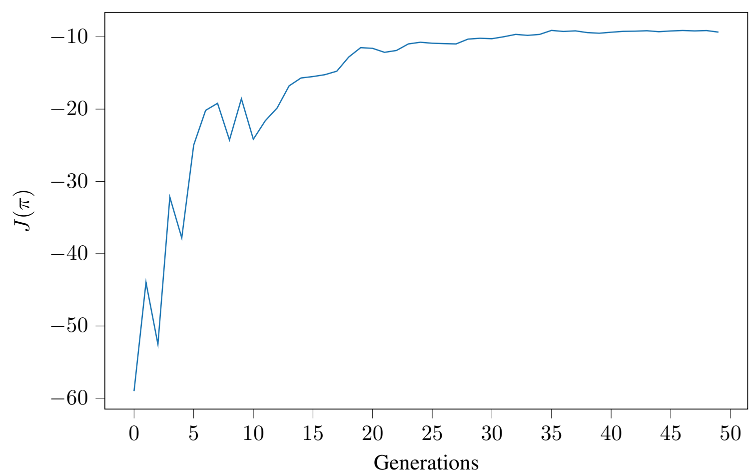

Figure 5: SAC best agent performance for each generation.

B.1 Linear Quadratic Gaussian Regulator

In this experiment, we consider a Linear Quadratic Gaussian (LQG) Regulator characterized as follows:

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \quad Q = 0.7 \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad R = 0.3 \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

Along each dimension, and for each time step t, the action a_t and the observation s_t, can take values in $[-3.5, 3.5]$, while the discount factor and the time horizon were set to $\gamma = 0.9$, and $T = 15$, respectively. We used a noise standard deviation as follows:

$$\sigma = 0.1 \cdot \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

We perform three experiments using three different seeds: 2, 42, 2022. We tune the hyper-parameters of SAC through the genetic algorithm described above, using as metric the empirical expected return. For all the seeds we consider, we used the hyper-parameters configuration space reported in Table 6. Notice that if only a single value is specified for its domain, it means that the hyper-parameter is considered fixed. The three runs performed (one for each seed) took on average 44 (± 17.2) hours each.

Table 7: Hyper-parameters configuration space for the HalfCheetah experiment.

Hyper-parameter	Search Space
Actor Learning Rate	$[10^{-5}, 10^{-2}]$
Actor Network	Two layers with 128 neurons and ReLU activations
Critic Learning Rate	$[10^{-5}, 10^{-2}]$
Critic Loss	MSE
Critic Optimizer	Adam
Critic Network	Two layers with 128 neurons and ReLU activations
Batch Size	[8, 256]
Initial Replay Size	[1000, 20000]
Max Replay Size	[10000, 1500000]
Tau	0.001
Policy delay	1
Policy	OrnsteinUhlenbeckPolicy(σ=0.2, θ=0.15, dt=10^{-2})
N Epochs	[1, 50]
N Steps	[1000, 15000]
N Steps Per Fit	[1, 10000]

In Figure 5 we report the value of the performance over time of the best agent of each generation for this experiment. It shows how the performances are almost constant in the last $\approx$ 25 generations, meaning that the optimization procedure converged to a solution near to a local minimum point. The scripts needed to run these three experiments (each corresponding to a different seed) are available at `https://github.com/arlo-lib/ARLO/tree/main/experiments/LQG`.

B.2 HalfCheetah

In this second experiment we used the simulated environment of HalfCheetah to run experiment on the model generation stage. The MDP corresponding to this environment is assumed to have a discount factor and a time horizon of $\gamma = 1$, and $T = 1000$, respectively. We perform three experiments using three different seeds: 2, 42, and 2022. We tune the hyper-parameters of DDPG using the genetic algorithm described above, considering as metric the Average Reward.

For all three seeds, we consider the hyper-parameters configuration space reported in Table 7. The three runs performed (one for each seed), took on average 124.7 (± 8.8) hours each. The scripts needed to run these three experiments (each corresponding to a different seed) are available at `https://github.com/arlo-lib/ARLO/tree/main/experiments/HalfCheetah-v3`.

B.3 Dam

In this experiment, we consider the control of a water reservoir (dam) that models the dynamics of a real alpine lake, as described by Castelletti et al. (2011). The observation space is a continuous space with 31 dimensions, each of which taking values in $\mathbb{R}^+$. This state space features represent the inflow values for the previous month. The action space is sampled to get a discrete space with 8 actions, each one corresponding to a different amount of water released in a day. The discount factor and the time horizon have been set to $\gamma = 0.999$ and $T = 360$, respectively. In this experiment, once we extract the dataset, we perform forward feature selection via mutual information, as described by Beraha et al. (2019). Hyper-parameters search space for the tested tunable feature selection unit is reported in Table 8.

Table 8: Hyper-parameters configuration space for the `Feature Engineering` stage of the Dam experiment.

Hyper-parameter	Search Space
K	{1, 2, 3, 4, 5, 10, 20, 50}
N Features	{1, 2, . . ., 31}

Once feature selection is performed, we fit a `Policy Generation` unit, i.e., FQI, using an Extremely Randomized Trees Regressor (Geurts et al., 2006) with the hyper-parameters present in Table 9. The entire run took around 2 hours. The script needed to run this experiment is available at `https://github.com/arlo-lib/ARLO/tree/main/experiments/Dam/dam.py`.

Table 9: Hyper-parameters used in the `Policy Generation` stage of the Dam experiment.

Hyper-parameter	Value
N Iterations	60
N Estimators	100
Criterion	MSE
Min Samples Split	10

C Additional Experiments

In this section, we present two additional experiments, the former implementing an offline pipeline (Section C.1), and the latter an online pipeline (Section C.2).

C.1 Offline Pipeline

The objective of this experiment to evaluate the capabilities of using the complete Offline Pipeline we defined in Section 4 in the Dam experiment described above (Section B.3).

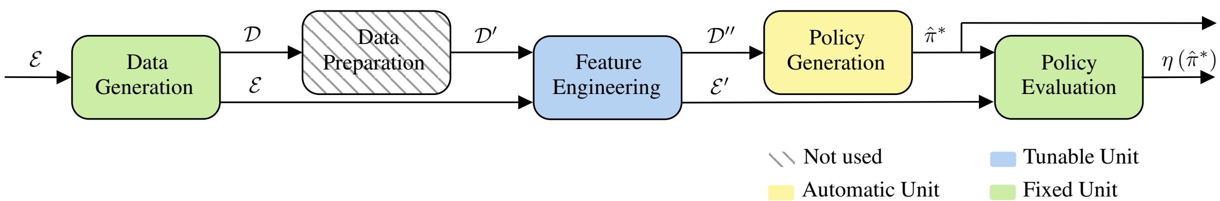

Figure 6: Types of the units adopted in the offline pipeline experiment.

Table 10: Hyper-parameters configuration space of XGBoost.

Hyper-parameter	Search Space
N Iterations	[2, 60]
N Estimators	[5, 250]
Min Child Weight	[1, 100]
Subsample	[0.5, 1]
Learning Rate	$[10^{-3}, 0.4]$
Max Depth	[4, 15]

Table 11: Hyper-parameters configuration space of ExtraTrees.

Hyper-parameter	Search Space
N Iterations	[2, 60]
N Estimators	[5, 250]
Criterion	MSE
Min Samples Split	[1, 50]

The scheme of the used pipeline and the topology of the different stages is presented in Figure 6. We use a fixed unit to generate the data, and a tunable unit to perform the `Feature Engineering` stage, as the ones we used for the dam experiment in Section 6. Subsequently, we use an automatic `Policy Generation` unit composed two tunable units using different versions of Fitted-Q Iteration, one with XGBoost as regressor, and the other with Extremely Randomized Trees. The two hyper-parameters configurations spaces are those presented in Table 10 and Table 11, respectively.

In Table 12 we report the empirical expected return over 10 episodes (standard deviation in brackets). Even though we have improved over the previously obtained result by about 20%, we point out that obtaining a statistically significant result would require a huge computational effort, indeed the entire run

Table 12: Results obtained for the additional experiment over the full offline pipeline.

Method	Empirical Expected Return
Baseline	-1224.67 (124.41)
Tuned Configuration	-1047.97 (213.37)

took around 16 hours. We leave to future experiments the test on a larger number of samples to assess the statistical significance of this result. The script needed to run this experiment is available at `https://github.com/arlo-lib/ARLO/blob/main/experiments/Dam/hp_tuning_fqi_dam.py`.

C.2 Online Pipeline

Differently from the previous experiments we run on online pipelines, in which we used a single tunable unit for the `Policy Generation` stage, in what follows, we apply an automatic unit to this stage, to tune the hyper-parameters of different algorithms. To test this out we run an automatic `Policy Generation` unit for the Linear Quadratic Gaussian Regulator, in which we tune both Soft Actor Critic (SAC, Haarnoja et al., 2018) and Proximal Policy Optimization (PPO, Schulman et al., 2017). To test the performance we consider the Discounted Reward (defined in Equation 1) in `Policy Evaluation` stage. Figure 7 represents the pipeline and the topology of the units used in the experiment.

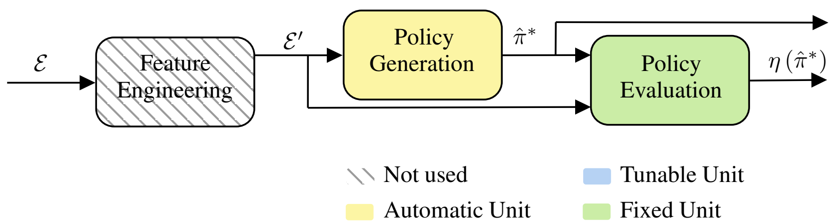

Figure 7: Types of the units adopted in the online pipeline experiment.

Table 13: Performance obtained using the automatic `Policy Generation` unit on the Linear Quadratic Gaussian Regulator.

Method	Empirical Expected Return
Van Dooren (1981)	-7.2 (4.9)
Best SAC Tuned Configuration	-8.2 (4.7)
Best Automatic Block Tuned Configuration	-7.4 (5.0)

Table 13 shows the results in terms of discounted reward. By tuning the hyper-parameters of two different `Policy Generation` tunable units the pipeline further improved the results presented in Section 6, reaching a level of performance in line with the one of the optimal solution by Van Dooren (1981).