**Intelligent Control**:

*Implementing Soft Actor-Critic (SAC) from Scratch*

*Description: Implement the SAC algorithm from scratch using PyTorch or JAX and apply it to robotics tasks. Analyze the impact of entropy regularization, target networks, and Q function stability.*

ΜΑRKANTONATOU EIRINI | up1095489

SOLOMONIDI ELEFTHERIA | up1092837

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**1. Introduction**

This project explores a model-free reinforcement learning (RL) approach for training an agent to interact with an environment and learn optimal behavior through experience. The main focus is the implementation of Soft-Actor-Critic (SAC) algorithm, an efficient off-policy algorithm designed for continuous action spaces. A central feature of SAC is entropy regularization which encourages the policy to remain stochastic and exploratory throughout training. The policy is trained to maximize a trade-off between expected return and entropy, a measure of randomness in the policy.

**2. Theoretical Foundations of SAC**

*Limitations of Standard Actor-Critic Methods*

Actor-Critic Algorithm is a type of reinforcement learning algorithm that combines two parts i.e the Actor which selects actions and the Critic which evaluates them. In many environments it works satisfactorily, but there are environments especially those with sparse rewards, the agent may prematurely converge to a suboptimal policy because it fails to adequately explore alternative strategies. This limited exploration leads to the risk of getting stuck in local optima and not explore alternative strategies that lead to better results. Another issue when using the Actor-Critic methods is that they often generalize poorly, as the actor tends to learn a single strategy that performs well during training but are no robust to unseen or slightly different situations.

These problems show why methods like Soft Actor-Critic (SAC), which focus on better exploration and randomness, are helpful in fixing these issues.

*Addressing issues with SAC*

In Soft-Actor-Critic algorithm instead of only asking the Actor to maximize it’s reward when training, the critic will ask the actor to do so while acting as randomly as possible. That is maximizing the entropy of its current policy. “Soft” refers to “entropy regularization”. The entropy of the policy being maximized, the actor is incentivized to explore alternative strategies and to recover from unexpected situations.

Consequently, it introduces a value function, the soft action – value function.

SAC parameterizes a policy and a soft Q- value function .

How does it work?

In SAC we use a policy iteration formulation, in which we evaluate the Q-function of the current policy and update the policy through an off policy gradient rule. In general Actor – Critic methods are derived from policy iteration, which alternates between **policy evaluation** and **policy imporovement** .

*Policy Evaluation*

Policy Evaluation is the initial step in reinforcement learning, involving the determination of the value function for a given policy.

In standard RL the policy evaluation optimizes only for rewards :

*Bellman Optimality Equation*:

**(2.1)**, where:

**(2.2)**

Instead in the policy evaluation step of soft policy iteration the policy is computed using the maximum entropy objective with the modified Bellman backup operator .

*Soft Bellman Equation:*

**(2.3)**, where:

**(2.4)**

Including the entropy term:

**(2.5)**,

the **uncertainty** or **randomness** of the policy’s action choices in a given state is quantified. The higher the entropy, the more spread out or exploratory the policy is.

Can entropy be whatever you want?

No. It is designed to measure uncertainty or randomness in a probability distribution. The term is the probability that the policy chooses action in .

* When is close to 1 is near 0 (high confidence)
* When is close to 0 is a large negative number (low confidence)
* **So is small for confident choices, large for unlikely ones**

Εικόνα που περιέχει κείμενο, γραμμή, γράφημα, διάγραμμα

Το περιεχόμενο που δημιουργείται από AI ενδέχεται να είναι εσφαλμένο.

Figure 1

This illustrates how SAC penalizes overconfident decisions to encourage exploration.

In SAC we want policies that balance high reward with high entropy. So penalizes overconfident actions and rewards diverse exploratory behavior.

*Policy Improvement*

Once the value function is evaluated, Policy Improvement follows. Consider a certain action in a state that has a higher expected reward than the current policy's action, then the policy is updated to choose the better action in that state.

In most RL algorithms the policy is improved using the following objective:

**(2.6)**

SAC changes that traditional MDP objective and converges to different solutions. The maximum entropy objective generalizes the standard objective (1) by adding an entropy term, such that the optimal policy additionally aims to maximize its entropy at each visited state:

**(2.7)**

Where a is called “temperature parameter” and controls the balance between reward maximization and exploration in the training process. This term determines the stochasticity of the optimal policy. Specifically:

* A higher α encourages more exploration, since the policy is rewarded for being more random.
* A lower α shifts the focus toward exploitation, where the policy sticks to high-reward actions.

*Iterative Soft Q-Value Optimization and Policy Update in SAC*

To optimize our action-value estimates, we employ the Bellman operator, which iteratively updates the soft Q-values for a fixed policy. Starting from any function and repeatedly applying Equation (2.3).

In the policy improvement step, we update the policy towards the exponential of the new soft Q function. We make actions that have higher soft Q-values more probable (softmax like update).

In reinforcement learning environments, actions can typically be either discrete or continuous. For discrete action spaces, action probabilities can be modeled directly using techniques like the softmax function. In contrast, continuous action spaces require modeling a probability density function, such as a Gaussian distribution.

A Gaussian Distribution is a common way to model continuous stochastic policies:

**(2.8)**,

where s is the current state.

Why are Gaussians tractable?

If you define a Gaussian as shown in Equation (2.8) then sampling an action is:

*(reparameterisation trick)*

Instead of sampling directly from a distribution (which is a non-differentiable operation) we apply the reparameterization trick. This technique expresses the random variable as a deterministic function of fixed random noise and learnable parameters, enabling gradients to flow through the sampling process.

Since in practice we prefer policies that are tractable we will restrict the policy to Gaussians. In the Soft Actor-Critic (SAC) algorithm, Gaussian distributions are used to represent stochastic policies in continuous action spaces.

*Policy Improvement Step*

The partition function Z normalizes the distribution, and while it is intractable in general, it does not contribute to the gradient with respect to the new policy and can thus be ignored.

Implementation:

3 Neural Networks. We will consider a parameterized soft Q-function, and a tractable policy ). The Q neural network is trained to approximate the **soft Bellman operator** while the policy network can be modeled as a Gaussian with mean and covariance given by neural networks:

: The most likely action

: randomness around that action

Why output instead of ?

* σ must be positive (it is a standard deviation)
* If you output it directly, your network might output negative or zero values, which would break the Gaussian:

3 objective functions:

**3. Environment Setup and Agent Dynamics**

*PointMaze Simulation Setup*

In the context of this project, the Gymnasium library was used, which provides simulation environments for reinforcement learning experiments. Specifically, the PointMaze environment was selected, simulating a maze where an agent must navigate from a randomly initialized starting position to a predetermined goal. The chosen environment is a two-dimensional horizontal maze in which the agent behaves like a point mass free to move along the x and y axes. At each time step, the agent observes its current **state** and selects an **action**, which influences its **next state** and the **reward** it will receive. Those key concepts are explained below:

*State*

The agent's state includes its current position (achieved\_goal) and the position of the desired goal (desired\_goal). The agent needs to know the desired goal at every step (a fixed and specific vector for each episode) because this determines where it should move and what it is trying to achieve. Especially in environments where the goal changes each episode, incorporating the desired goal is necessary for learning a policy that can generalize to different targets.

*Action*

The agent’s action represents the linear force applied to the point mass in the x and y directions, moving it to the next state. At each time step, the agent selects an action corresponding to a continuous change in its position within the maze. Once an action is selected, the agent transitions to the next state, receives a reward, and a signal indicating whether the episode is done.

*Reward*

The reward function used in this environment is based on **sparse rewards**. Specifically, the agent receives a reward if and only if it reaches the goal (the ball is considered to have reached the goal when the Euclidean distance is less than 0.5 m), while all intermediate steps yield zero reward. This makes the learning process more challenging, as the agent does not receive direct feedback on whether it is moving in the right direction or not. Learning is primarily based on a few but crucial experiences where the agent achieves the goal. Despite the use of sparse rewards, the Soft Actor-Critic (SAC) algorithm manages to learn effectively, mainly thanks to the use of **replay buffer**.

*Replay Buffer*

The replay buffer stores all the agent’s **experiences (state, action, reward, next state, done)** at each step of the episode, allowing successful experiences to be reused. During training, the agent samples randomly from the buffer, selecting mini-batches of experiences according to a predefined batch size. This way, the information about "success" is not lost but can reappear multiple times, gradually strengthening the agent’s policy. When an experience includes reaching the goal (i.e., a high reward), the Q-network is updated. Specifically, the Q-value increases because the target equation

Q(sₜ, aₜ) = r + γ ·Q(sₜ+1, π(sₜ+1)) (3.1)

includes a high reward r. The Q-network (the Critic) gradually learns that certain state-action pairs lead to high rewards. At the same time, the policy network (the Actor) is trained to select actions that maximize the Q-value—those most likely to result in successful transitions. As a result, the probability that the agent will reproduce success increases, even in environments with sparse rewards.