Solving Complex Sparse Reinforcement Learning Environments

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# **Objective**

In this project, we will try to extend the current state-of-the-art systems to solve complex sparse reinforcement learning tasks. In many real-world scenarios, an agent faces the challenge of sparse extrinsic reward, leading to a problematic and challenging objective to solve. The idea behind these scenarios is that the reward is rare and usually found after a complex series of events. Therefore, discovering this reward by random exploration is unfeasible, especially for complex environments.

We will build on top of SAC-X [1], a technique proposed to solve these tasks by creating auxiliary policies that allow the agent to efficiently explore the environment. In the paper the authors test the algorithm for the task of stacking two objects and clean-up. We will try to analyze the algorithm on a more complex task of object grasping and manipulation, e.g., cube manipulation with a robotic hand and identify the potential shortcomings of this algorithm and explore advances to it.

# **Related Work**

Various approaches have been proposed to solve for the sparse reward problems

## Reward shaping

This was the first idea introduced to solve the problem [2]. The idea is including additional reward features to reward or punish interactions with the environment. This requires hand-crafted reward functions by domain experts which may introduce a human bias to the possible policies learnt by the agent i.e. overfitting to the rewards found in the environment or not exploring good policies unknown to humans and thereby limiting the learning of the agent. So, this sparse setting is very useful to avoid reward shaping.

## Curiosity driven methods

In this approach, the agent must explore the environment in order to discover the final reward state. Therefore, curiosity must be modelled as a reward signal. There have been several contributions following this idea. For instance, curiosity can be seen as an intrinsic reward for the agent [3] or we may create self-supervised exploration [4].

## Curriculum learning

The idea is presenting the agent increasingly complex tasks over time until it is able to solve the initial sparse task. One technique used for curriculum learning is GoalGAN which uses a Generative Advesarial Network to create new goals that are harder but still solvable for the agent [5]. Curriculum learning, on the other side, does either need a human to design specific base tasks or has restrictive requirements for the task to make human interaction unnecessary.

## Auxiliary tasks

Agent will explore the environment until the external reward is found based on the auxiliary tasks presented to the agent Jaderberg et al. [6]. Though it will continue to follow the base agent’s policy but updating the shared components not only helps learn auxiliary tasks but also better equip the agent to solve the overall problem by extracting relevant information from the environment. Riedmiller et al [1] put forward Scheduled Auxiliary Control (SAC-X) an extension using unsupervised auxiliary tasks.

# **Technical Outline**

We plan to re-implement the SAC-X paper and investigate an extension on the task of cube manipulation with a robotic hand. The milestones for our project are:

* Developing a toy environment according to OpenAI Guidelines which is defined as follows: square world(grey 10 X 10 grids) with only three different grids of different color (blue, red, green). The agent’s task will be to reach the colored grids in some specific order say green then blue then red. First, the position of the agent and color grids will be fixed. After optimizing the agent for the task on these fixed positions we will then later randomize these position in the environment. The observations may consist of the agent's as well as the three colored grid positions, the action is the position delta of the agent. For the agent to optimize it’s position on the three subtasks to optimize the overall performance.
* Once the environment is built, we will implement the benchmark algorithms presented in by Riedmiller et al. [1] to solve for the toy problem mentioned above.
* Then, when everything is set up in a toy environment, we will investigate how the presented method can be used for finer and more dexterous object manipulation e.g. a hand grasping and rotating a cube. In this case, the agent will only receive an external reward after achieving a specific position.
* In a final step, we will explore on how to advance the existing implementation to achieve better performance in our object manipulation task. For instance, we could try to implement recurrent neural networks such as LSTM to impose temporal consistency for moves. This might be really important for real-world scenarios in which uncoordinated actions can result on failure. For example, when rotating a cube if a finger is lifted before the previous one was placed in its final position this will result on the cube falling.

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