Rover-Arm

1. Abstract

The task of organizing and arranging objects in a room can be a tedious and time-consuming process. We present the RoverArm project, which aims to develop a robotic system capable of autonomously picking up and arranging objects using reinforcement learning techniques. The project is divided into multiple tasks, starting with the ability to pick up a single object, which is the goal of the first version of the project. A Gym Environment is created to facilitate training of the robotic arm and has been published as a PyPi package.

We explore various reinforcement learning algorithms, including DQN, DDPG, Advantage Actor Critic (A2C), and Proximal Policy Optimization (PPO). Additionally, we experiment with different neural network variations, such as simple Multi-Layer Perceptron (MLP), DQN-style architecture, Qt-Opt with numeric observations added layer-wise and concatenated, as well as Vision Transformer (VIT) models.

2. Environment and Task

The RoverArm project utilizes a simulated environment in the OpenAI Gym framework to train and evaluate the robotic arm's object manipulation capabilities. The task of the bot is to navigate close enough and pick up the object. The environment provides visual and numeric observations, including front and top views of the scene and tray, along with coordinates of rover, end effector, and object. If the bot gets close to the object it gets a small positive reward (say 0.001) and if it gets far it gets a negative reward, once the object is picked it gets a large positive reward (+1). The action space is a six-dimensional box, ranging from -1 to 1, encompassing rover actions (throttle, steer) and arm actions (dx, dy, dz for end effector coordinates, and f for finger location).

3. Reinforcement Learning - Online Models

a. Algorithms

I have experimented with DQN, DDPG - Actor critic (base version), Advantage Actor Critic, and PPO. Since, A2C and PPO are expected to work better and due to training time constraints and GPU limitations, I have majorly trained on A2C and PPO.

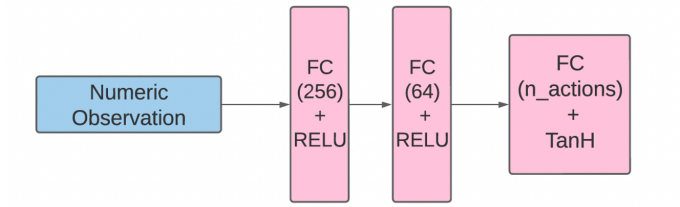
DQN - The output of neural network is n_actions * actions_per_dimension no. of values, where each action is discretized into actions_per_dimension categories and we take softmax across actions_per_dimension values to get n_actions maximum actions.

Actor Critic and PPO models - The outputs of the Actor network are two n_actions dimensional vectors, one for mean which comes from NN model, and one for standard deviation which is kept constant in Actor Critic and comes from model in PPO. We use the mean and standard deviation to sample the action. The Critic Network always outputs a single value, V function value of the state.

b. Neural Network Architectures

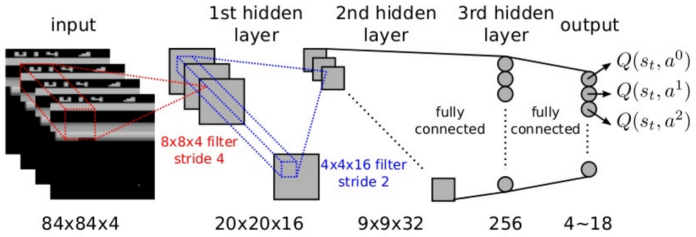
I. Simple MLP

Numeric Observation is passed through a set of fully connected layers and RELU activation except for the final layer where Tanh is used for the activation layer.



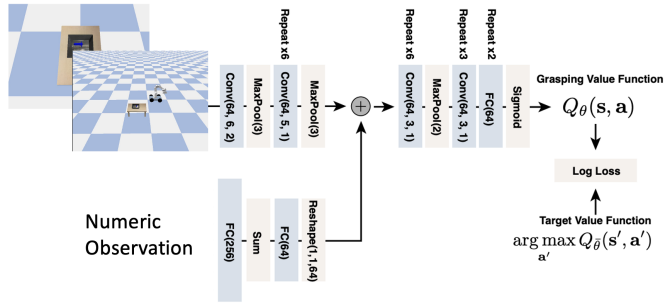
II. DQN Style

Observation (only front view of scene) is taken, converted to gray scale image. The last 4 frames of the environment are joined and passed to the NN. A set of convolutional layers followed by fully connected layers are used.



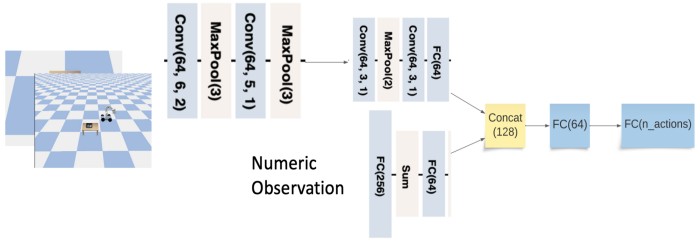
III. Stand Qt-Opt Style

Observation (the front view of scene and top view of tray, 6 channels image) is passed through a set of conv + max pool layers and numeric observation is passed through FC + Relu layers and both the outputs are added layerwise and this vector is passed through a set conv + max pool layers and then FC + Relu and finally one FC + tanh.



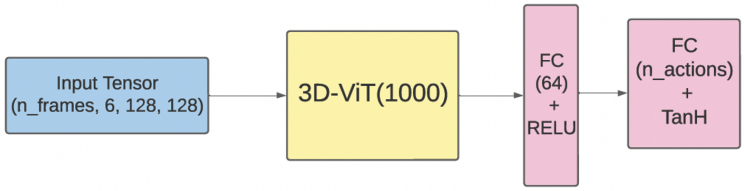
IV. Modified Qt_Opt Style

Observation (the front view of scene and top view of tray, 6 channels image), goes through a similar process as above except that Numeric observation is concatenated instead of addition. Also, this model is altered to take n frames as input, so the input image of 6*n_frames channels is passed as the first conv layer's input.



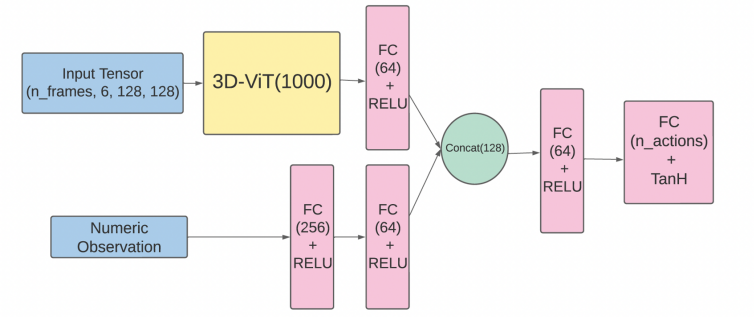
V. 3D-ViT

Observation (n_frames of 6 channel image) is passed through the VIT block, which outputs an encoded vector of size 1000 and which is passed to FC + RELU and then FC + Tanh layers.



VI. 3D-ViT + Numeric Observations

Observation (n_frames of 6 channel image) is passed through the VIT block, which outputs an encoded vector of size 1000 and which is passed to FC + RELU, the numeric observation goes through set of FC layers and then both are concatenated and this is passed to set of FC layers.



c. Training

The simplest task of the environment (navigating and picking the object from the tray) is quite complex because it takes at least 3000-5000 steps when the task is performed by a human. Therefore, it requires large amounts of data to be trained, and large models like ViT that support the retention of such information. These models take at least 40-50 hours to get trained for 100 episodes of 2000 steps. Detailed training times can be found in the table below.

MODEL	EPISODES	STEPS	Observed TRAINING TIME	Expected training (100 episodes)
A2C_Simple	200	2000	2HOURS	1Hour
PPO_Simple	200	2000	2HOURS	1Hour
A2C_1_DQN	50	2000	6HOURS	12Hours
A2C_2 – QT OPT	100	2000	22HOURS	22HOURS
A2C_3 – QT OPT + OBS CONCAT	100	2000	16HOURS	16HOURS
A2C – VIT2 (OBS CONCAT)	80	2000	32HOURS	40HOURS
A2C – VIT1	10	2000	6HOURS	60HOURS

4. Offline Models - With Expert Training

The major problem with online training for the rover-arm tasks is that until the end goal is reached, the agent wouldn't have seen the final state, in which the actual reward is obtained. In this situation the bot has to navigate to the object, hold it, and pick it up, where almost never happens. So, the best way is to generate the data offline and to train the model with that data.

Data Collection

The bot is configured to be controlled by keyboard. For every step, the (state, action, reward, is_done, next_state) is recorded. It takes around 2000-4000 steps depending on the starting position of the bot to complete an episode when the task is performed by an expert.
All these lists' of pairs for multiple episodes are added to a list called expert_buffer. More than 100 episodes have been recorded into this expert_buffer, and this data is used for training the model.

Limitation: The real-time keyboard control isn't possible if the images are rendered, because the pybullet rendering is extremely slow when the images are converted into rgb_arrays. Hence only the numeric observations are recorded, and variations of neural networks are limited with this dataset.

a. Simple Actor Critic with Expert Training

Training Strategy: We maintain two buffers, a replay buffer and an expert buffer. At each step, we sample 25% of the batch from the replay buffer and 75% from the expert buffer. This way the model learns more from the expert data and which teaches it to perform in the expert's way. This 25, 75% can be considered as hyper-parameters and could be fine-tined for better performance.

With a batch size of 512, we train a simple multi-layer perceptron that takes only numeric observation as input (not the image of rgb array).

b. Decision Transformers

Decision Transformers are a type of neural network architecture that combines the strengths of Transformers and Reinforcement Learning to make sequential decisions. They capture long-range dependencies and learn to make optimal decisions in a variety of tasks such as game playing and robotic control.

Training:

The 100+ hand crafted episodes stored into numpy arrays are converted into arrow dataset format, which is passed to DecisionTransformerGymDataCollator to transform the data into a compatible format for the hugging face model that is used.

The model receives input sequences (full episodes) and encodes them using self-attention mechanisms, capturing dependencies and relationships between elements.

The key concept of decision transformers is that the model is trained to teach the agent to achieve the desired reward rather than maximizing reward, which implies that all training the trajectories should be as optimal as possible for best performance. This makes it even harder for the learning process to happen.

5. Future Plan

- **Data Augmentation**

The major problem with the training is the amount of data that has been present. While generating more data manually and hand crafting policies are possible options, these are tedious and practically not possible on a large scale. Proper data augmentation could definitely improve the performance of the agent.

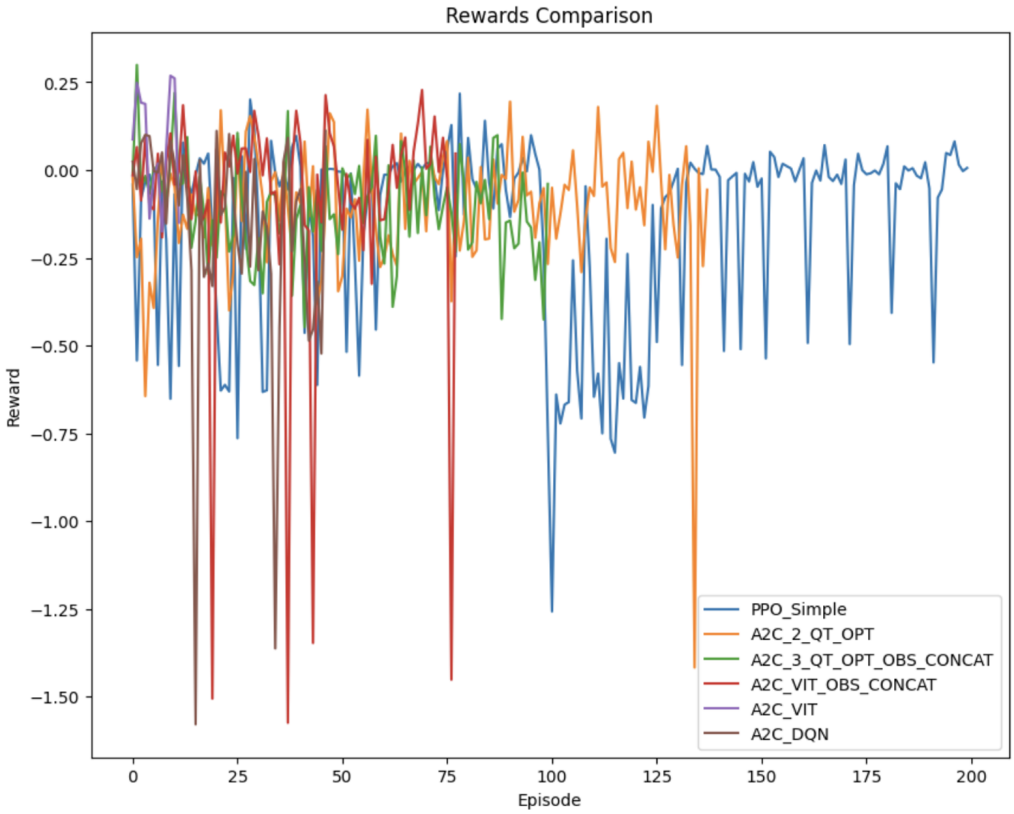
- **Dyna-Q with Diffusion**

With the recent breakthrough of diffusion models for image generation, we could use this ability to train a dynamics model that could predict the next state and reward given state and action. In cases where the amount of data present is not huge, model based learning could help the agent make better decisions with extra data and perform better. Moreover, the ability of diffusion is fascinating and using that in reinforcement learning could be a great research area to explore.

6. Results and Conclusion

A plot of Episode Reward vs Episode has been shown on the right. The poor performance is majorly due to the lack of training data. If the model is provided with more hand crafted examples or expert trained data, it could perform better. Even with state of the art models like decision transformers, the agent couldn't learn to complete the task, so we could understand that 100+ episodes data is not enough for a complex task like this. We need more ways to augment the dataset and efficient ways to generate data.

Yet, we can observe that the rover navigates towards the object and the arm tries to get close to the object in some instances.



7. Code and Output

The environment and training code with other details can be found in this repository.
Saiphani724/RoverArm: A OpenAI Gym Env for Rover with Arm (github.com)

Link to Training Codes - https://github.com/Saiphani724/RoverArm/tree/main/training
Env PyPI Package - https://pypi.org/project/rover-arm/
Output Samples - https://github.com/Saiphani724/RoverArm/tree/main/output
Ppt link - https://1drv.ms/p/s!Aswo8fN5BKr61klitElDnhZ-JARq

8. References

a. DQN - [1312.5602] Playing Atari with Deep Reinforcement Learning (arxiv.org)

b. DDPG - [1509.02971] Continuous control with deep reinforcement learning (arxiv.org)

b. A2C - [1602.01783] Asynchronous Methods for Deep Reinforcement Learning (arxiv.org)

c. Qt-Opt - [1806.10293] QT-Opt: Scalable Deep Reinforcement Learning for Vision-Based Robotic Manipulation (arxiv.org)

e. TorchRL PPO - Reinforcement Learning (PPO) with TorchRL Tutorial

f. ViT Pytorch Code - lucidrains/vit-pytorch: Implementation of Vision Transformer

g. Hugging face decision transformer - Train your first Decision Transformer (huggingface.co)

h. Decision Transformer Paper - 2106.01345.pdf (arxiv.org)