Extend deepbots to support stable-baselines and implement gym-style default Reinforcement Learning environments

Sanket Kumar Thakur,

sanketkumar1996@gmail.com | sanket.thakur@iit.it PhD student, Istituto Italiano di tecnologia (University of Genova) Genova

About Me : Resume

Stay connected :



Contribution :

- Develop RL based environments which are based on openAI gym scenarios (<u>https://gym.openai.com/envs/#classic_control</u>).
 - LunarLander-v2 using the Mavic 2 robot. Develop the robot nodes in deepbots framework as well. The environment has continuous states and discrete action space. It can be solved using PPO which is already implemented <u>here</u> and is one of the stable-baseline. My <u>Reference solution</u> using DQN.
 - MountainCarCountinous-v0 which can be used with <u>BB-8</u> robot. Discrete action based mountaincar have already been resolved here(<u>pitescape</u>). Similar environment can be used for the continuous action space. This environment can be solved with either DDPG. A similar solution has been implemented for <u>CartPole-continuous using DDPG</u>. My <u>Reference solution</u> for mountainCarCountinous using CEM.
- The environments should be enhanced to support following categories :
 - \circ continuous state, discrete action space $\ -$ LunarLander, Acrobot
 - Continuous state action space MountainCarContinous-v2
 - Discrete space action Create a new simple testbed env different from the gym environment. Can I create <u>Taxi-v3</u> using <u>ALTINA</u> and solve it using simple q-learning ?? (We can implement a simple FetchPush-v1 environment similar to this <u>implementation</u>. But I am not sure if to keep this in the proposal. I'd like to work on a snake implementation. Also, you mentioned integrating Ray for hyper parameter optimization I do not have much

experience with that, maybe you could perhaps provide some ideas on it, I can add to the timeline if it seems feasible.

- Other ideas :
 - Snake : The environment can be a simple snake game using <u>salamander</u> with the position of the snake's head, its length and its distance (Euclidean) from the bait constituting as state observations and the actions being turn left, up, down or right (4). The reward is provided for most bait eaten. - Continuous state, discrete action. The environment can be solved using DQN, which is already implemented <u>here</u>.
- Develop a universal script to support users to install all the environments.
- Properly document the use of environment and algorithms to support users in their own implementation. Also, create easy-to-use methods and classes to help others tweak with the hyperparameter optimization of the algorithms and states of the environment.
- Tech Stack and tools :
 - Python
 - Pytorch
 - Pipenv, mypy

Timeline :

- Community Bonding weeks : Study the robot-supervisor scheme wonderfully described here and get used to the web bots framework. Develop a basic environment or the one mentioned in the tutorial using different sensors. Communicate doubts regarding the framework with mentors and create a blueprint for the environments that are to be targeted. Also discuss a testbed environment that can be built without referring to the gym and targeting the discrete space-action space.
- Week 1 2 : Work on the first environment project and add controllers to the robots. Create the robot controller and supervisory scripts for robot control and states.

- Week 3 : Decoding bugs and checking the code to make sure the agents work properly and the states are properly transmitted through the framework.
- Week 4 5 : Work on the second environment project along with their necessary scripts. Develop the robot node definition in deepbots.
- Week 6 : Submit the mid level evaluation results and progress.
- Week 7 : Spare week if delays from week 4 spill-over. Discuss other stable-baseline methods(DQN) which can be added to the codebase. Develop a concrete design for the custom testbed. Also, consider adding an infrastructure for hyper parameter optimization. We can decide if to work on adding a baseline method or instead on the hyperparams optimization using ray.
- Week 8 10 : Develop the "new" environment robot node definition and its related scripts and controllers based on robot-supervisor method.
- Week 11 : Spare week in case of work getting delayed, solving bugs and decoding the codebase.
- Week 12 : Prepare and submit the final evaluation results.

Am I good enough ?

• I have previous experience in building a python environment and then using it to train a RL agent. <u>Dino AI</u> - where I created a simple clone of google chrome game.



So, I have 5 value based state objects and 3 actions (0 - nothing to do, 1 - jump, 2crouch, it might vary for two agent scripts). The results are here. <u>https://www.youtube.com/watch?v=mrzyq8SkX0A</u>

- I have worked on the mentioned algorithms using openAl gym environment and maintain a github repo while applying the algorithms on different gym based environments. Check it here. <u>https://github.com/sanketsans/openAlenv</u>
- I am also currently in top leaderboards for some openai gym environments.

Why am I doing this ?

- I am really excited about Reinforcement Learning and especially its applications in human-level intelligence in games. I was fortunate enough to work with RL during my internship and since then I try to learn new algorithms and implement them in a gym based environment or other simple environment which either I find on github or I create them.
- I recently found out about deepbots and it seems exciting to me and since it is still growing, I believe it can give me an opportunity to work on different RL environments while working on open-source.
- Finally, GSOC is a really great opportunity to indulge myself into open source contribution and connect with mentors and like-minded people to establish connections and obviously help the community.
- Besides, I will want to stay with the organization in future as well.

Reference:

1. Mnih, V., Kavukcuoglu, K., Silver, D. *et al.* Human-level control through deep reinforcement learning. *Nature* **518**, 529–533 (2015). <u>https://doi.org/10.1038/nature14236</u>