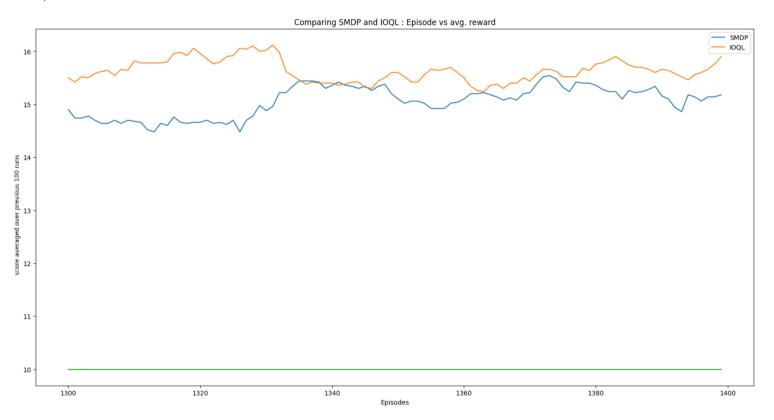
RL | PA -3: SMDP & Intra-Options Q-learning | Report

By, Chandresh Sutariya (21f3001415)

Colab link: https://colab.research.google.com/drive/1Pu0wWvtX9--MVL5DjSzXuF5D7JmnRgfN?usp=sharing

Comparison between SMDP & IOQL



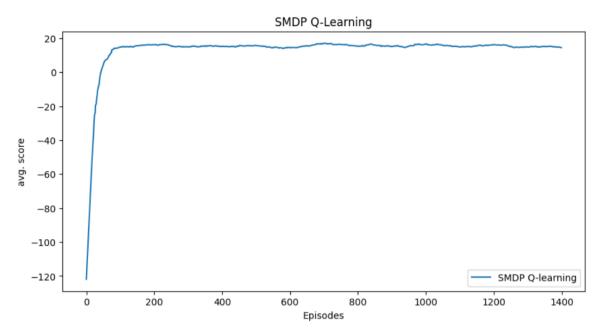
In this particular task/environment, I observed that IOQL's and SMDP-Q-Learning's rewards do not differ significantly.

I tried running the whole notebook several times to see if the reward curves change significantly, but they were the same (of course at a high level view).

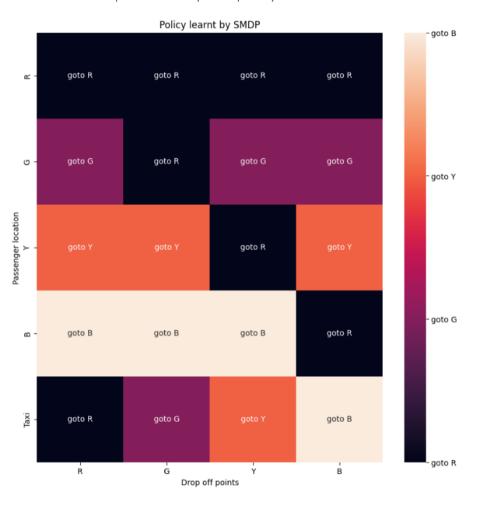
While running the notebook several times and observing, I saw that the-number-of-times the Q-leaning gives slightly better rewards were more. This may be because, in Q-learning, we update the option q-value regardless if the option is ending or not, but in SMDP, that is not the case. In SMDP we only update the q-value of the option when the option is terminating.

The one reason I think that both IOQL and SMDP-QL give the same reward curves is that the task here is very small, there are not many options and the options themselves are also small (in terms of actions that the option has). AND the policy learned by both algorithms is also the same, I think that is also due to the same reason.

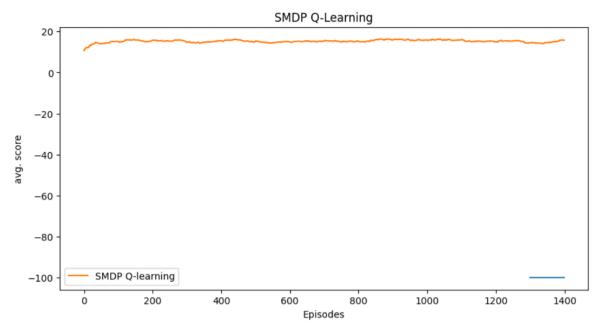
Task 1: SMDP | Reward Curve while learning



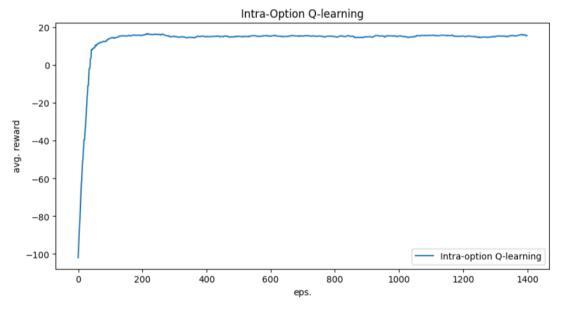
Task 1 : SMDP | Learned Option policy



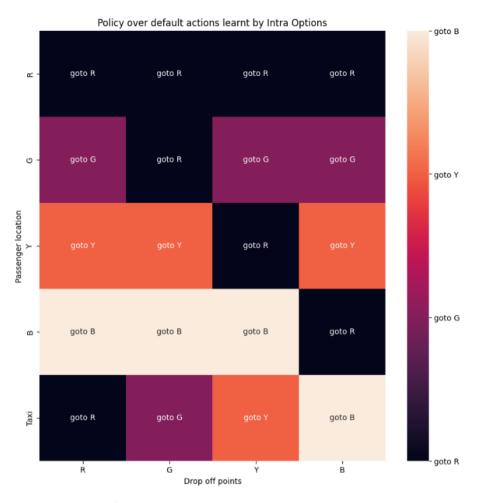
Task 1: SMDP | Reward Curve after learning (using learned Q-values) (not updating SMDP Q-values)



Task 2: SMDP | Reward Curve while learning



Task 2 : SMDP | Learned Option policy



Task 2 : SMDP | Reward Curve after learning (using learned Q-values) (not updating SMDP Q-values)

