– GridWorld –

Installation:

From Zip file	From Github

`unzip GridWorld-master.zip`
`cd GridWorld-master`
`pip install -r Requirements.txt`
`python setup.py install`
	`git clone https://github.com/prasenjit52282/GridWorld.git`
	`cd GridWorld`
	`pip install -r Requirements.txt`
	`python setup.py install`

Tested Software/Hardware Setup:

The project is implemented with **Python 3.9.x** along with numpy and pygame library to construct the GridWorld class. All library requirements are listed in the “Requirements.txt” file of the codebase. The algorithms are trained on a **MacBook M1 Air** (with 8GB primary memory running MacOS v13.4 with base-kernel version: 22.5.0).

Classical RL:

1. Create a **Gridworld environment** with holes and unsafe states.
2. **Implement** the Policy Evaluation, Policy Iteration, Value Iteration, Safe Monte-Carlo (MC) Learning, Safe Temporal-Difference (TD, **SARSA chosen**) Learning algorithms.
3. **Compare the results from the above algorithms**, and give insights why the results are better or worse for one algorithm compared to others.

Deep RL:

1. Create a **Gridworld environment** with holes and unsafe states.You have to create a large **discrete** (**40x40**) **gridworld** or a continuous Gridworld. Instead of being a single cell, each hole should be a **hole region**. The goal will also be a **goal region**.
2. Implement **DQN, NPG, TRPO and PPO** algorithms.
3. Compare the results from the above algorithms, and give insights why the results are better or worse for one algorithm compared to others.
4. Design a **visualization tool** for rendering how the algorithm controls the robot. The rendering function should preferably be part of the Environment Class. This will help demonstrate the agent's actions.

CRL: Objective 1:

After installing the tool, we can import and create a gridworld environment as follow:

```
from gridworld import GridWorld

world=\
    """
    wwwwwwwwwwwwwwwww
    wa          o    w
    w     o          w
    www       wwwwwwww
    w       o wg     w
    wwwww     ww   www
    w  o             w
    w         wwwwwwww
    w            o   w
    wwwwwwwwwwwwwwwww
    """

env=GridWorld(world,slip=0.2,log=False,max_episode_step=1000)
```

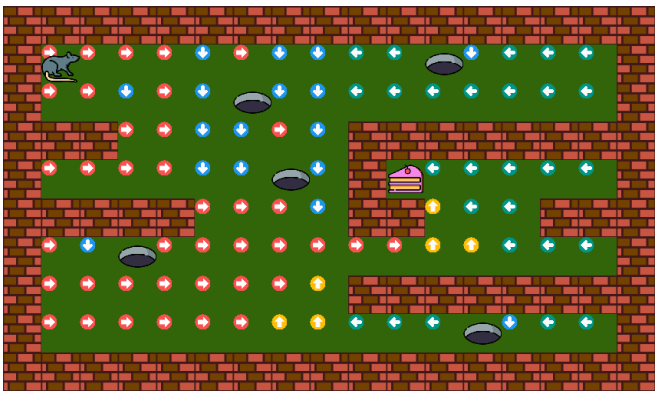


Fig. 1: Creating environment

Here “a” means Agent, “g” means Goal, “w” means Wall, “o” means Hole. The environment builds the transition probability matrix (P_sas) and the reward matrix (R_sa) from the defined string pattern to test Model-based algorithms. Moreover, for model-free algorithms, the tool provides an openAI-gym like interface to interact with the environment and explore.

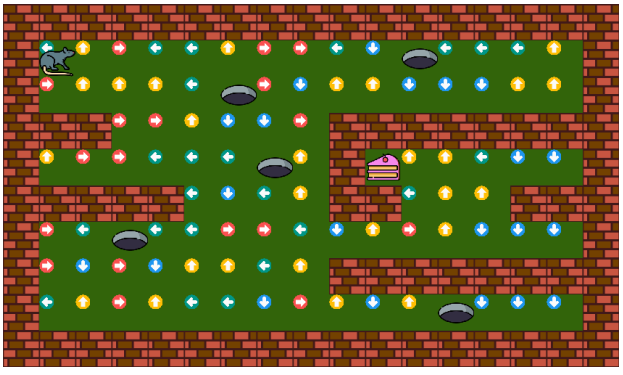
CRL: Objective 2:
“examples” folder in the codebase contains the desired Reinforcement Learning algorithms that are tested on this gridworld tool. Run the algorithms as follow:

- **Policy Evaluation**
  - `python example/policy_eval.py`
- **Policy Iteration**
  - `python example/policy_itr.py`
- **Value Iteration**
  - `python example/value_itr.py`
- **Safe Monte-Carlo**
  - `python example/safe_mc.py`
- **Safe SARSA**
  - `python example/safe_sarsa.py`

The underlined gridworld environment object is defined in "examples/gridenv.py", and the logs of each algorithm are stored in the "logs" folder of the codebase.

Definition> Safety
Unsafe probability “H_sa[s,a]” of taking an action “a” from state “s” is defined as the probability of falling in a hole at (1/(1-gamma_risk)th future state. For safe Monti-Carlo gamma_risk=1.0 (end of episode) and for safe SARSA gamma_risk=0.66 (3 future states).

CRL: Objective 3:
Note: The actions mappings are {0:'right',1:'down',2:'left',3:'up'}



Selected policy

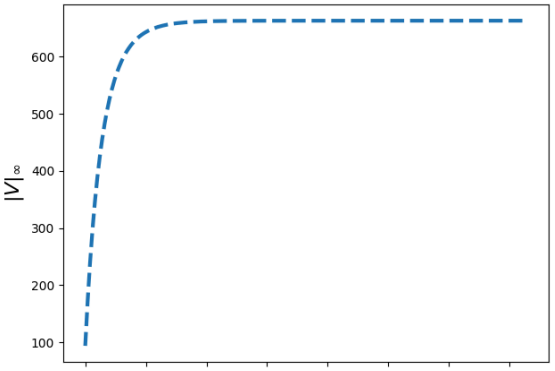


Fig. 2: Policy Evaluation

i) Policy Evaluation: A random policy is selected as shown in Fig 2. The Policy Evaluation algorithm converged in **183 iterations** with epsilon 1e-07 ($|V_{n+1}-V_n|$<epsilon).

ii) Policy Iteration: Policy Iteration converged in **20 iterations** (Pi_{n+1}=Pi_n) with final policy as Pi_*= [0 0 0 0 1 0 1 1 2 2 2 1 2 2 2 0 0 1 0 1 1 1 1 2 2 2 2 2 2 0 0 1 1 0 1 0 0 0 0 1 1 1 1 1 2 2 2 2 2 0 0 0 1 3 2 2 0 1 0 0 0 0 0 0 0 0 3 3 2 2 2 0 0 0 0 0 0 0 3 0 0 0 0 0 0 3 3 2 2 2 2 1 2 2] as shown in Fig 3.

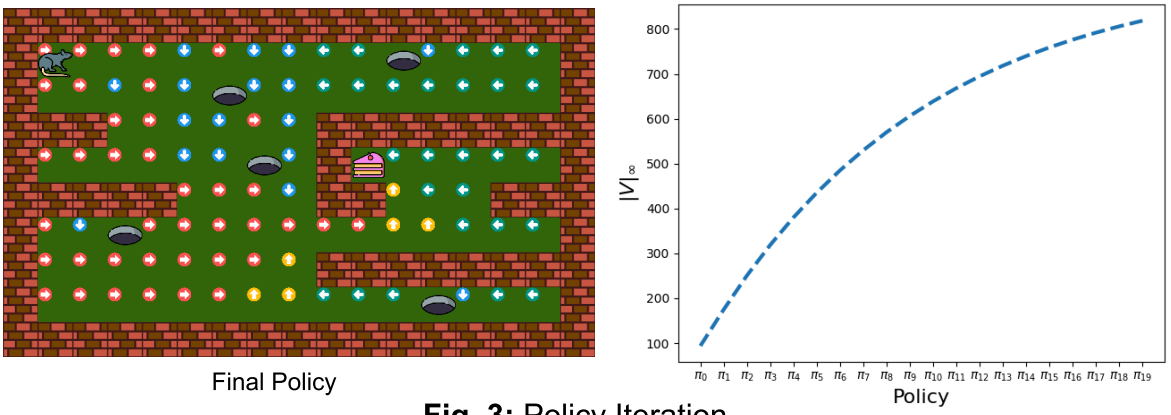


Fig. 3: Policy Iteration

iii) Value Iteration: Value Iteration converged to **epsilon-optimal** ($|V_*-V_n|$<epsilon) solution in **159 iterations** with eps 0.0001 Pi_*= [0 0 0 0 0 0 1 1 2 2 2 1 2 2 2 0 0 1 0 1 1 1 1 2 2 2 2 2 2 2 0 0 1 1 0 1 0 0 0 0 1 1 1 1 1 2 2 2 2 2 0 0 0 1 3 2 2 0 1 0 0 0 0 0 0 0 0 3 3 2 2 2 0 0 0 0 0 0 0 3 0 0 0 0 0 0 3 3 2 2 2 2 1 2 2] as shown in Fig 4.

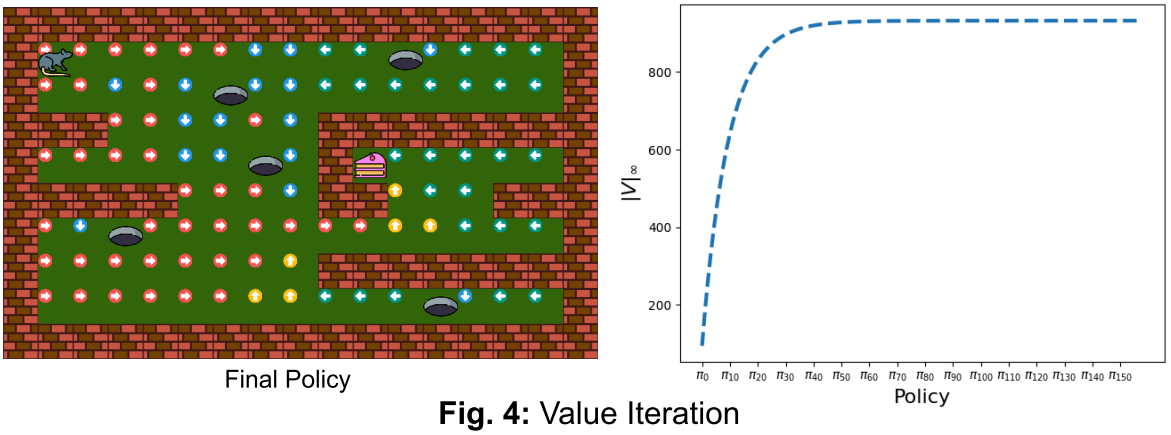


Fig. 4: Value Iteration

Policy Iteration v/s Value Iteration:

Both of the algorithms provide an all state optimal policy, however **Value iteration results in a superior policy** as shown in Fig. 3 and Fig 4. The infinity norm of value is greater in case of Value iteration. However, Value iteration takes **159 iterations** to converge as compared to Policy iteration which converges in only **20 iterations**. *This Policy Iteration is much more efficient but produces a slightly suboptimal policy than Value iteration.*

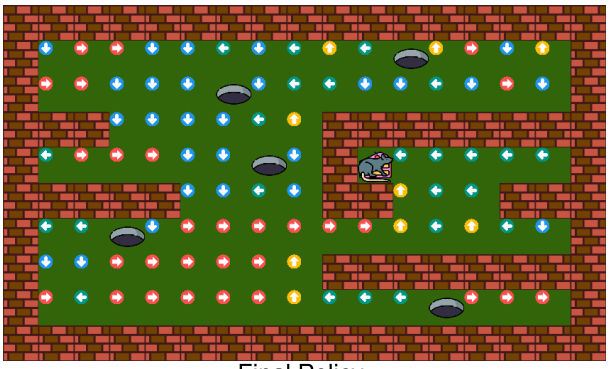
iv) Safe Monte-Carlo Control:

Hyperparametes:

gamma=0.99, alpha=1e-4 (learning rate), beta=0.999 (1-beta is learning rate for H_sa), **unsafe_prob=0.1**, episodes=100000, steady_explore_episode=30000

Epsilon is linearly decayed from 1 to 0.01 in first 30000 episodes then stays constant.

Pi= [1, 0, 0, 1, 1, 2, 1, 2, 3, 2, 0, 3, 0, 1, 3, 0, 0, 1, 1, 1, 0, 1, 2, 2, 1, 1, 2, 1, 0, 1, 1, 1, 1, 1, 2, 3, 2, 0, 0, 0, 1, 1, 0, 1, 0, 2, 2, 2, 2, 2, 1, 1, 2, 1, 3, 2, 2, 2, 2, 0, 1, 0, 0, 0, 0, 0, 0, 3, 2, 3, 2, 1, 1, 1, 0, 0, 0, 0, 0, 3, 0, 2, 0, 0, 0, 0, 0, 3, 2, 2, 2, 0, 0, 0, 0] as shown in Fig 5.



Final Policy

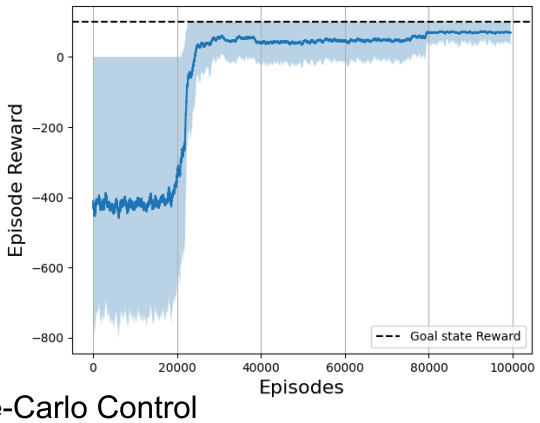


Fig. 5: Safe Monte-Carlo Control

Test runs:
Episode 0 Total reward 79
Episode 1 Total reward 76
Episode 2 Total reward 69
Episode 3 Total reward 73
Episode 4 Total reward 74
Episode 5 Total reward 79
Episode 6 Total reward 82
Episode 7 Total reward 72
Episode 8 Total reward 78
Episode 9 Total reward 71

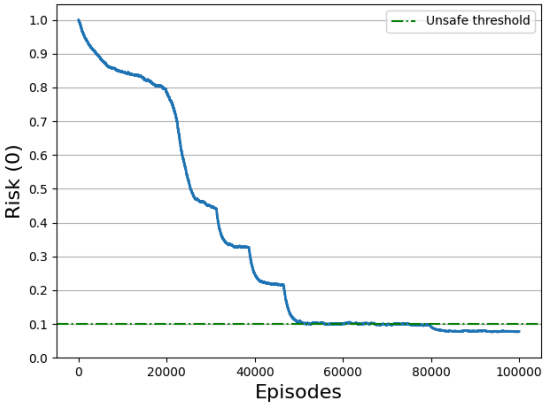


Fig. 6: Risk of falling from Start State (0)

v) Temporal Difference Learning (SARSA):

Hyperparametes:

gamma=0.99, gamma_risk=0.66 (3 future states), alpha=1e-3 (learning rate), **unsafe_prob=0.1**, train_steps=2000000, steady_explore_step=100000

Epsilon is linearly decayed from 1 to 0.01 in first 100000 interactions then stays constant.

Pi= [0, 0, 1, 1, 2, 0, 0, 3, 3, 2, 0, 3, 3, 2, 2, 0, 0, 1, 1, 2, 0, 0, 3, 1, 2, 2, 1, 1, 0, 0, 0, 1, 1, 2, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 2, 2, 2, 2, 2, 2, 1, 1, 0, 1, 3, 2, 2, 3, 1, 0, 0, 0, 0, 0, 0, 0, 0, 3, 2, 2, 2, 3, 3, 1, 0, 0, 3, 3, 3, 3, 2, 2, 2, 3, 3, 3, 3, 3, 2, 3, 2, 0, 0, 0, 0] as shown in Fig 8.

Test runs:
Episode 0 Total reward 81
Episode 1 Total reward 79
Episode 2 Total reward 80
Episode 3 Total reward 80
Episode 4 Total reward 77
Episode 5 Total reward 81
Episode 6 Total reward 74
Episode 7 Total reward 81
Episode 8 Total reward 77
Episode 9 Total reward 74

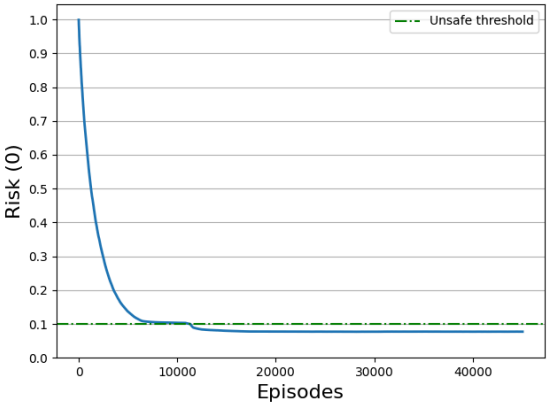


Fig. 7: Risk of falling from Start State (0)

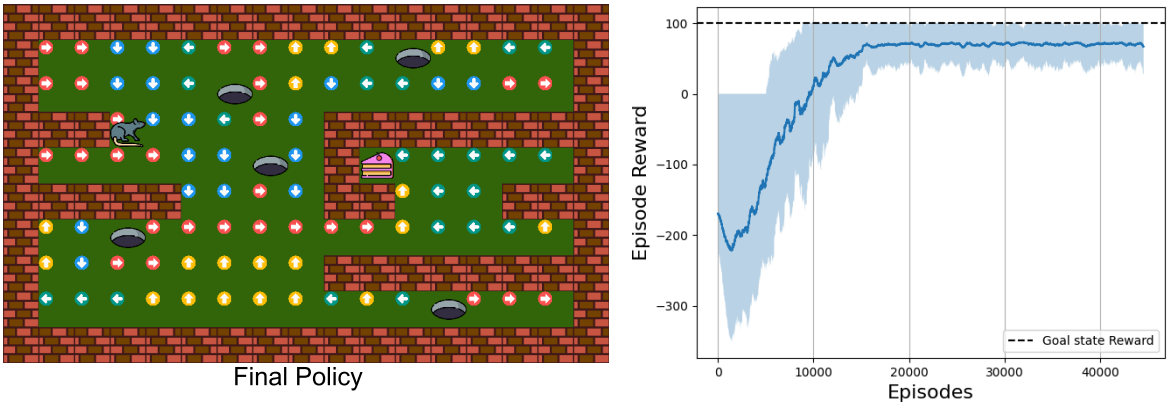


Fig. 8: SARSA (TD learning)

Monte-Carlo v/s SARSA

Both the algorithms give optimal Q values only for the states that occur frequently in the optimal path towards the goal. While satisfying the safety constraints **(10% falling rate at max)** as shown in Fig 6 and Fig 7**,** the SARSA **(20000 episodes)** algorithm converges quicker as it bootstraps the Q values thus faces less variance and stabilises earlier than Monte-Carlo **(80000 episodes)**. Thus **SARSA is efficient and performs similar** to Monte-Carlo in terms of game playing in the gridworld environment. Observing the final policies, we can say that both the algorithms come up with a path to *reach the goal as fast as possible while staying away from the holes*.

Model-based v/s Model-free

Despite that the model-based algorithms (Policy iteration, Value iteration) give the optimal policy in very few iterations as compared to model-free algorithms (Monte-Carlo, SARSA), model-based algorithms require the complete knowledge of the underline environment (P_sas, R_sa) to come up with a solution. However, most of the time we do not have the complete model of the environment. This is why model-free algorithms are more applicable in the real-world.

DRL: Objective 1:

After installing the tool, we can import and create a discrete gridworld with a string pattern shown in **examples/library/gridenv.py**

“a” means Agent, “g” means Goal, “w” means Wall, “o” means Hole. The goal and hole/trap **region can be represented with a blob** of the character in the string pattern as shown in the above file.

To make an environment compatible with DRL, pass isDRL as True in the GridWorld constructor.

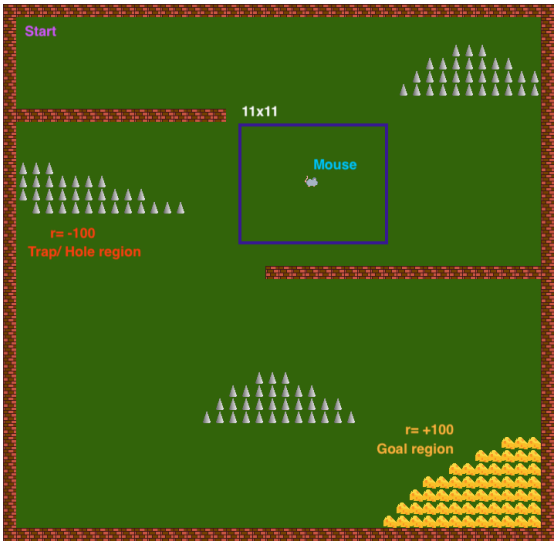


Fig. 1: 40x40 environment

DRL: Objective 2:

“examples” folder in the codebase contains the desired Reinforcement Learning algorithms that are tested on this gridworld tool. Run the algorithms as follow:

- **Deep Q Networks**
  - `python examples/dqn.py`
- **Natural Policy Gradient**
  - `python examples/npg.py`
- **Trust Region Policy Gradient**
  - `python examples/trpo.py`
- **Proximal Policy Gradient**
  - `python examples/ppo.py`

`Testing on saved model:`

```
python examples/[algo_name].py --init_from_exp [ALGO_NAME] --test --render
# example: python examples/ppo.py --init_from_exp PPO --test --render
```

The underlined gridworld environment object is defined in "**examples/library/gridenv.py**", and the logs of each algorithm are stored in the "logs" folder of the codebase.

DRL: Objective 3:

Note: The actions mappings are {0:'right',1:'down',2:'left',3:'up'}, I have used the ractGridWorld wrapper implemented in the GridWorld package. Thus, one action is repeated (repeat=**4**) time, and the corresponding state observations are stacked together to make the effective state representation (shape: 11x11x4 = **484**)

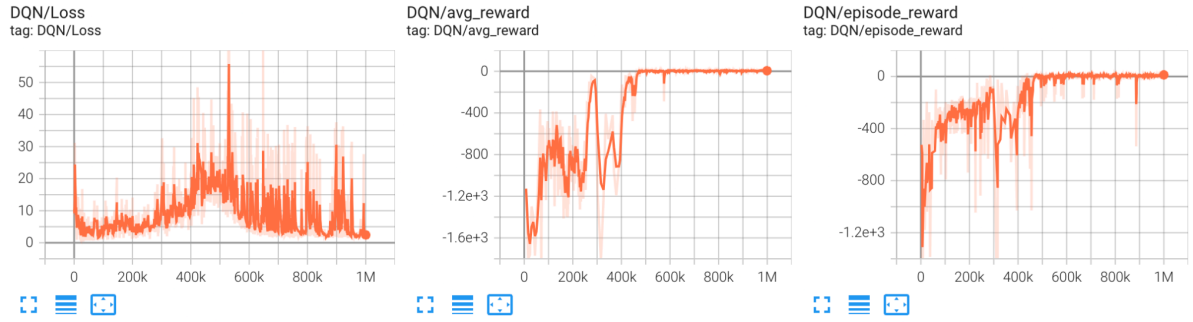


Fig. 2: DQN performance

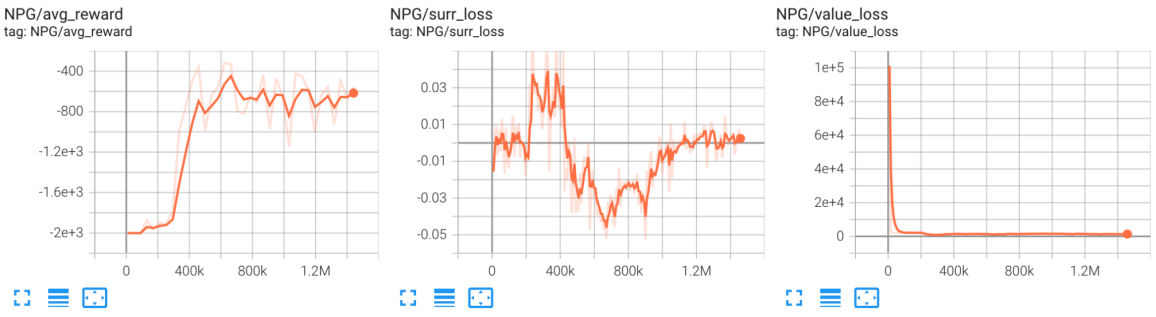


Fig. 3: NPG Performance

i) DQN: As shown in Figure 2, DQN converged with maximal performance among the above DRL algorithms (**avg reward of -1.2 for 10 runs**) in **1M steps**. It solves the environment and reaches the goal region. (See recorded video)

ii) NPG: As shown in Figure 3, NPG converged with minimal performance among the above DRL algorithms (**avg reward of -314.2 for 10 runs**) in more than **1M steps**. It does not solve the environment and falls into a trap/ hole region. (See recorded video)

iii) TRPO: As shown in Figure 4, TRPO converged with moderate performance among the above DRL algorithms (**avg reward of -67.6 for 10 runs**) in more than **1M steps**. It solves the environment. (See recorded video)

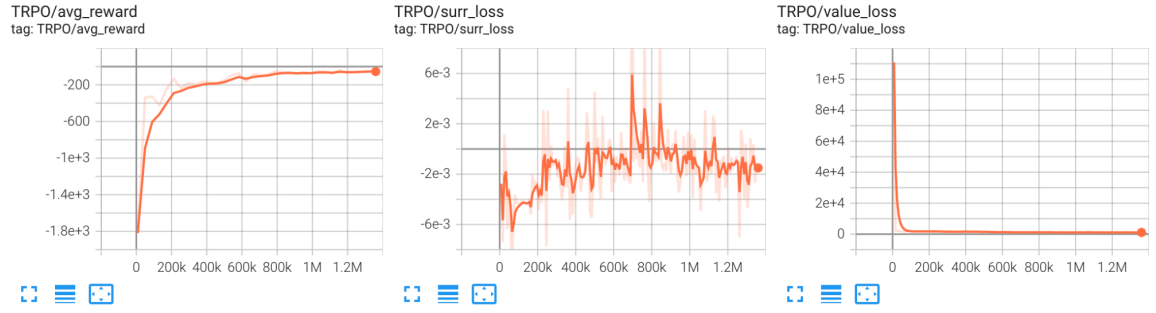


Fig. 4: TRPO Performance

iv) PPO: As shown in Figure 5, PPO converged with close to DQN level (best) performance among the above DRL algorithms (**avg reward of -11.6 for 10 runs**) in only **500k steps**. It solves the environment. (See recorded video)

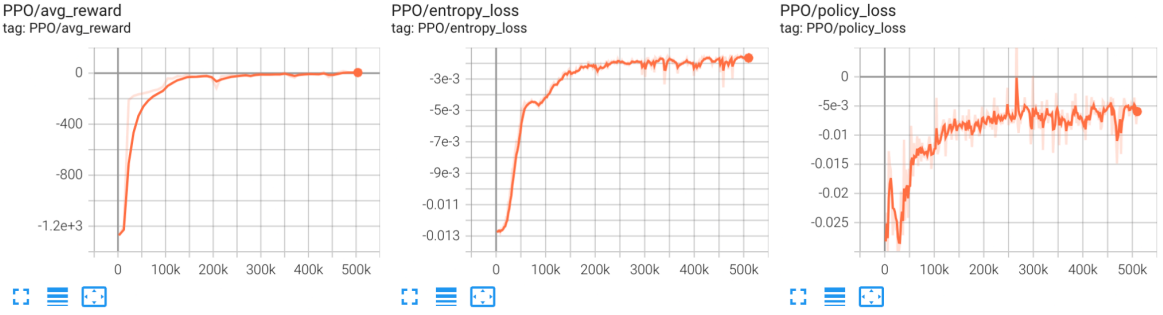


Fig. 5: PPO Performance

DQN vs PPO

Both the algorithms solved the given gridworld with almost similar performance. However, **DQN solves for a global optimality** due to complete off-policy training. Whereas, PPO is constrained with the collected data in each iteration from the current policy.
Hence **PPO solves for a local optimality** and might never reach DQN level performance. In contrast to DQN, **PPO is very fast in convergence** and has better convergence guarantee statistically. Thus, **PPO is more practical** and widely adapted in real-world RL implementations. *Note that in our experiments, DQN took **45 mins** to converge where PPO took only **10 mins**.*

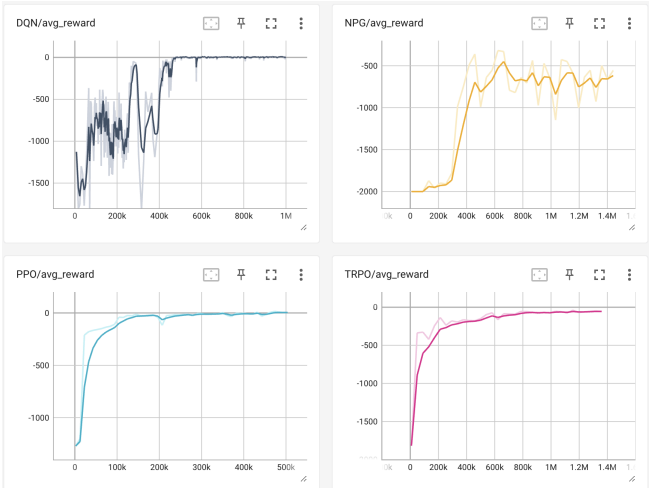


Fig. 6: Comparison

NPG vs TRPO vs PPO

NPG does not solve the environment due to **high approximation error in the Hessian Matrix** of KL divergence and direct update. Whereas, TRPO improved upon the updates with a **linesearch** for reducing noisy updates from Hassian and **importance sampling** in the policy gradient. However, due to second order differential over all network parameters, *both the algorithms are infeasible for larger networks or will take too much resources to train.*

PPO constrains the KL divergence with **importance ratio clipping** and achieves similar convergence properties with first order differentiation. Thus, among three algorithms, *PPO is the most advanced* and *NPG is the first to introduce the idea of trust region updates. Note that in our experiments, NPG and TRPO took **21 mins** to converge where PPO only took **10 mins**.*

DRL: Objective 4:

While testing the policy, we can just uncomment the “env.render()” line to have a visualisation of the agent interacting with the environment.

```
report=""
pi_report=f"Pi= {pi}\n\nTest runs:"
report+=pi_report+"\n"
print(pi_report)
for e in range(10):
    done=False
    total_reward=0
    s=env.reset()
    while not done:
        a=pi[s]
        #env.render()
        s_,r,done,info=env.step(a)
        total_reward+=r
        s=s_
    epi_report=f"Episode {e} Total reward {total_reward}"
    report+=epi_report+"\n"
    print(epi_report)
env.close()
```

Renders the environment

References

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3. Silver, D., Graves, A., Antonoglou, I., Riedmiller, M., Mnih, V., Wierstra, D. and Kavukcuoglu, K., 2013. Playing atari with deep reinforcement learning. DeepMind Lab. arXiv, 1312.
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