Reinforcement Learning for Games

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Abstract:

The main idea behind this project is to understand one of the booming fields of artificial intelligence which is Reinforcement Learning. First and foremost, we understand the basic terminologies and the concepts of Reinforcement learning. The problems of Reinforcement learning is formulated as a Markov Decision Process (MDP). Then, we move to intermediate level, to understand more about the value function and policy function. The topics that are main focused in this project are Q learning, Deep Q Learning using Deep Learning networks. With respect to this project, I have created the tutorial blog series to capture my understanding and help other beginners to kickstart in the field of Reinforcement Learning. The links to my articles are mentioned in the below section

Tutorial Series Created

1. https://medium.com/@nancyjemi/basics-reinforcement-learning-66aae5da4c85
2. https://medium.com/@nancyjemi/level-up-understanding-q-learning-cf739867eb1d
3. https://medium.com/@nancyjemi/deep-q-learning-explained-65df980aac6f

Key Terminologies

These are the most common terminologies that are used when we start talking about RL

State: The current situation of the agent.

Action: The decision or the move made by the agent to change its current state to future state

Environment: The place where the agent interacts and performs the action, the environment can be physical or virtual

Agent: The one that we train in our Reinforcement Learning problem to tackle the environment.

Reward: The feedback given to the agent after the move from the current state to the future state. The feedback signal is scalar.

Policy: Optimal policy which is formulated as a strategy, that an agent adopts from moving from one state to another.

Value function: The reward that an agent would get by taking an action in the current state to move to the next future state.

Markov Decision Process

All our problems in Reinforcement learning can be formulated as a Markov decision process. An MDP consists of a set of finite environment states S, a set of possible actions A(s) in each state, a real-valued reward function R(s), and a transition model P(s', s | a). However, real-world environments are more likely to lack any prior knowledge of environment dynamics.

Therefore MDP and agent together give rise to a sequence or trajectory that begins like this:

S0, A0, R1, S1, A1, R2, S2, A2, R3,…..

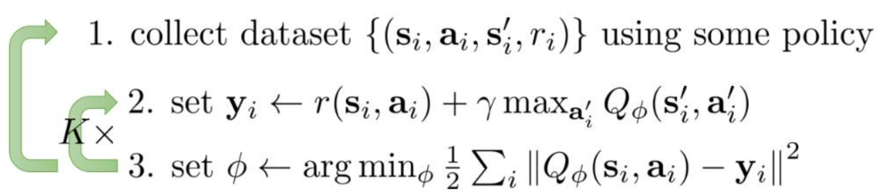
Implementation

The implementation of q-learning algorithm pseudocode is given below,

The Bellman equation for the action-value function is:

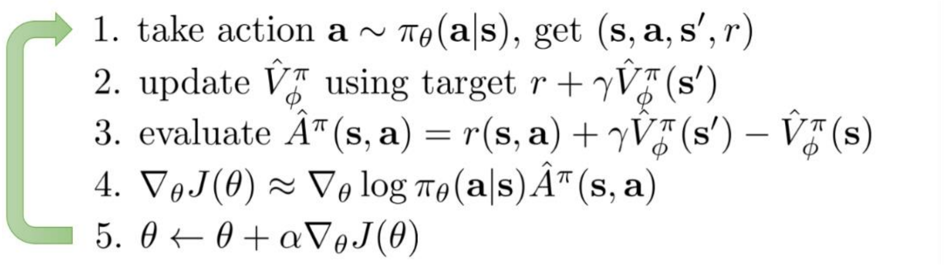
$$\begin{aligned} q_*(s,a) &= \mathbb{E}\Big[R_{t+1} + \gamma \max_{a'} q_*(S_{t+1},a') \,\Big|\, S_t = s, A_t = a\Big] \\ &= \sum_{s',r} p(s',r \mid s,a)\Big[r + \gamma \max_{a'} q_*(s',a')\Big], \end{aligned}$$

Estimate the action-value function ***Q*** with a model parameterized by *Φ*.



```
1. collect dataset $\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$ using some policy
  $K\times$
    2. set $\mathbf{y}_i \leftarrow r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \max_{\mathbf{a}'_i} Q_\phi(\mathbf{s}'_i, \mathbf{a}'_i)$
    3. set $\phi \leftarrow \arg\min_\phi \frac{1}{2} \sum_i \|Q_\phi(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{y}_i\|^2$
```

Full fitted Q-iteration source



```
1. take action $\mathbf{a} \sim \pi_\theta(\mathbf{a}|\mathbf{s})$, get $(\mathbf{s}, \mathbf{a}, \mathbf{s}', r)$
2. update $\hat{V}^\pi_\phi$ using target $r + \gamma \hat{V}^\pi_\phi(\mathbf{s}')$
3. evaluate $\hat{A}^\pi(\mathbf{s}, \mathbf{a}) = r(\mathbf{s}, \mathbf{a}) + \gamma \hat{V}^\pi_\phi(\mathbf{s}') - \hat{V}^\pi_\phi(\mathbf{s})$
4. $\nabla_\theta J(\theta) \approx \nabla_\theta \log \pi_\theta(\mathbf{a}|\mathbf{s}) \hat{A}^\pi(\mathbf{s}, \mathbf{a})$
5. $\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$
```

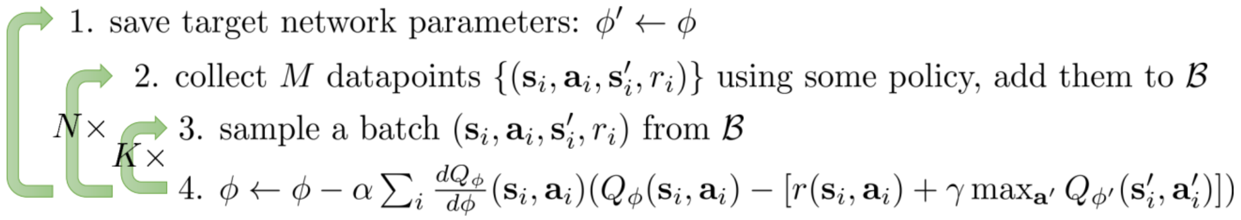
Online Q-iteration source

The above-mentioned implementation is done in by jupyter notebook.

Deep Q Learning algorithm Pseudocode

Q-learning with replay buffer and the target network

Add a replay buffer and a target network for training stability.

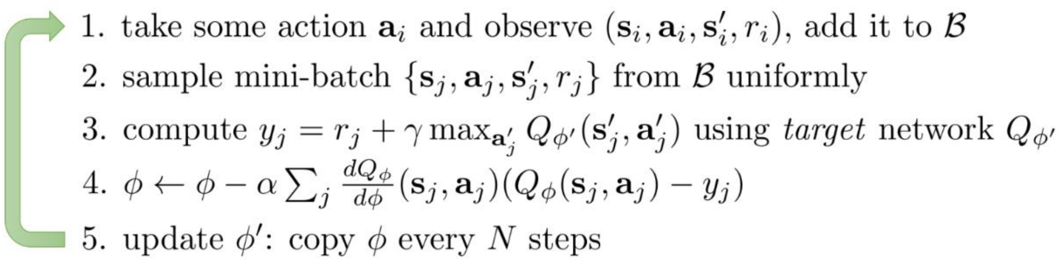


```
$N\times$
1. save target network parameters: $\phi' \leftarrow \phi$
    2. collect $M$ datapoints $\{(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)\}$ using some policy, add them to $\mathcal{B}$
    $K\times$
        3. sample a batch $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$ from $\mathcal{B}$
        4. $\phi \leftarrow \phi - \alpha \sum_i \frac{dQ_\phi}{d\phi}(\mathbf{s}_i, \mathbf{a}_i)(Q_\phi(\mathbf{s}_i, \mathbf{a}_i) - [r(\mathbf{s}_i, \mathbf{a}_i) + \gamma \max_{\mathbf{a}'} Q_{\phi'}(\mathbf{s}'_i, \mathbf{a}'_i)])$
```

Source

DQN (Deep Q-learning)

DQN is a Q-learning method with a deep network to estimate ***Q*** using a replay buffer and a target network.



```
1. take some action $\mathbf{a}_i$ and observe $(\mathbf{s}_i, \mathbf{a}_i, \mathbf{s}'_i, r_i)$, add it to $\mathcal{B}$
2. sample mini-batch $\{\mathbf{s}_j, \mathbf{a}_j, \mathbf{s}'_j, r_j\}$ from $\mathcal{B}$ uniformly
3. compute $y_j = r_j + \gamma \max_{\mathbf{a}'_j} Q_{\phi'}(\mathbf{s}'_j, \mathbf{a}'_j)$ using *target* network $Q_{\phi'}$
4. $\phi \leftarrow \phi - \alpha \sum_j \frac{dQ_\phi}{d\phi}(\mathbf{s}_j, \mathbf{a}_j)(Q_\phi(\mathbf{s}_j, \mathbf{a}_j) - y_j)$
5. update $\phi'$: copy $\phi$ every $N$ steps
```

Source

Important hyperparameters

Q- learning parameter optimization Strategy

The values of **`alpha`, `gamma`, and `epsilon`** were mostly based on intuition and some “hit and trial”, but there are better ways to come up with good values.

Ideally, all three should decrease over time because as the agent continues to learn, it actually builds up more resilient priors

- **α:** (the learning rate) should decrease as you continue to gain a larger and larger knowledge base. The learning rate should be in the range of 0 -1. The higher the learning rate, it quickly replaces the new q value. We need to optimize it in a way so that our agent learns from the previous q values. A learning rate is a tool that can be used to find how much we keep our previous knowledge of our experience that needs to keep for our state-action pairs.

- **γ:** as you get closer and closer to the deadline, your preference for near-term reward should increase, as you won’t be around long enough to get the long-term reward, which means your gamma should decrease.

- **ϵ:** as we develop our strategy, we have less need for exploration and more exploitation to get more utility from our policy, so as trials increase, epsilon should decrease.

Deep Q learning parameter optimization

state_size = [84, 84, 4] — Our input is a stack of 4 frames hence 84x84x4 (Width, height, channels)
action_size = env.action_space.n — no of possible actions
learning_rate = 0.00025 — Alpha (aka learning rate)

total_episodes = 100 — training episode count
max_steps = 50000 — maximum steps are taken at each episode
batch_size = 64 — training sample in the batch

explore_start = 1.0 — exploration probability at start
explore_stop = 0.01 — minimum exploration probability
decay_rate = 0.00001 — exponential decay rate for exploration prob

gamma = 0.9 — Discounting rate

pretrain_length = batch_size — Number of experiences stored in the Memory when initialized for the first time
memory_size = 1000000 — Number of experiences the Memory can keep

stack_size = 4- Number of frames stacked

Conclusion

This is the blog that inspired me to create my article with the concepts which I have understood from reading the source available. I have tried to recreate the first three tutorial of this link in my article. Please have a look at it and provide with the feedback and also assessments for each articles are created at the end of each blog.

https://www.freecodecamp.org/news/diving-deeper-into-reinforcement-learning-with-q-learning-c18d0db58efe/

The **terminologies and the taxonomy of the Reinforcement Learning** is covered in this report. The main areas that I have concentrated are

1. Q learning
2. Deep Q learning

Environment used are from openai gym and retro - Taxi, Mountain Car, CartPole

All the problem in the Reinforcement Learning is considered as a **Markov Decision Process .**

This process consists of set of states, actions and the rewards. **The goal of the Reinforcement Learning is to maximize the reward that the agent** receives in the future. The main idea to this is **the Reward Hypothesis**.

In the real-world, **we can define our Rewards to the environment** in which we want to train our agent

Q-learning – Can be used in the environment where the state space is discrete.

Deep Q learning – Can be used in the environment where the state space is continuous and for that we implement the deep learning model to calculate our Q value for every iteration of state-action pairs.

Q learning is the model free, off policy algorithm, The Q learning is improved by the trail and error method.

Reference & Citations

- https://www.freecodecamp.org/news/diving-deeper-into-reinforcement-learning-with-q-learning-c18d0db58efe/
- https://towardsdatascience.com/introduction-to-various-reinforcement-learning-algorithms-i-q-learning-sarsa-dqn-ddpg-72a5e0cb6287
- https://deeplizard.com/learn/video/ewRw996uevM

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