Atari Breakout Reinforcement Learning Environment

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Abstract

Atari Breakout environment implementation and training an agent using multiple algorithms over a generated environment (changing brick layouts)

1. Introduction

Our project is implementing an Atari breakout environment and training an agent to play it across general levels. The project repository can be found here: `https://github.com/duoduocai-dot/csc498-project` To play the original game, after cloning the project, just run this file: `https://github.com/duoduocai-dot/csc498-project/blob/main/run_Breakout.py`.
Our environment is here. We made a made our environment embedded into a pygame class for Breakout, adding environment functions and variables.
We made 6 algorithms which play Breakout, and compare their performance in this report. The algorithms we made are: DQN, double-DQN, policy gradient REINFORCE, tabular Q-Learning, tabular double Q-Learning, and tabular SARSA.

2. Environment

Our environment is here: `https://github.com/duoduocai-dot/csc498-project/blob/main/breakout.py`.

2.1 Rewards

We experimented with various reward mechanisms. Our original reward schema was:

- +10 for ball hitting paddle
- -10 ball missing paddle
- +1 ball hits brick
- -0.2 movement penalty
- +1000 ball destroys all bricks

However, with this model we noticed it was difficult for the agent to actually learn, as it doesn't get direct feedback if making an action is good or not. So we altered the reward schema to be:

- +10 for ball hitting paddle
- -10 ball missing paddle
- Distance between paddle and ball in the x-Axis `https://github.com/duoduocai-dot/csc498-project/blob/main/breakout.py#L179`
- +1000 ball destroys all bricks

2.2 Environment variables, functions

Regarding the rest of the environment, the step function is here, where the paddle moves depending on the action passed in, and updates rewards for that step. It then returns the game state which is [paddle x-location, ball x-location, ball y-location,ball x-speed, ball y-speed, bricks left].
The reset function resets the environment, setting ball, bricks, paddle to their original position.
Render functio, renders the game. Make function creates the brick layout, and main function allows the user to play the game.
Agent actions are to move left (0), move right (1), stay still (2).
There is more about the environment including the brickLayout which we used in testing and comparing the tabular algorithms which I will talk about in that section.

3. Algorithims

3.1 Tabular Algorithms

We made 3 algorithms which utilize a tabular setup. We reduced the state sizes such that they could be discretized, and fit inside a table.

How we created the tabular setup is by first getting every possible paddle and ball locations using this discretizeStateSpaceAllStates function which splits the paddle x-locations into 20 possible locations, the ball x-locations into 80 possible locations, and ball y-locations into 30 possible locations. The game screen is 800x600 and paddle is 80 wide and ball is 5x5.

I experimented with 3 different schemas to discretize the state space. These included:

- 10 paddle locations, 40 ball x-locations, 20 ball y-locations
- 10 paddle locations, 80 ball x-locations, 30 ball y-locations
- 20 paddle locations, 80 ball x-locations, 30 ball y-locations

The last one with the most paddle and ball locations worked best:

Here are the rewards from the last 10 episodes of training using the fewest number of states (first bullet):

```
episode = 9990, epsilon = 0.0009000000000938177, rewards =  -41954
episode = 9991, epsilon = 0.0008000000000938177, rewards =  -33707
episode = 9992, epsilon = 0.0007000000000938176, rewards =  -41622
episode = 9993, epsilon = 0.0006000000000938176, rewards =  -48913
episode = 9994, epsilon = 0.0005000000000938175, rewards =  -42440
episode = 9995, epsilon = 0.0004000000000938175, rewards =  -269565
episode = 9996, epsilon = 0.0003000000000938176, rewards =  -31498
episode = 9997, epsilon = 0.0002000000000938176, rewards =  -59294
episode = 9998, epsilon = 0.0001000000000938176, rewards =  -26515
episode = 9999, epsilon = 9.381755897326649e-14, rewards =  -36514
```

Compared the rewards from the last 10 episodes of training using the most states (last bullet):

```
episode = 9990, epsilon = 0.0009000000000938177, rewards =  -29335
episode = 9991, epsilon = 0.0008000000000938177, rewards =  -37168
episode = 9992, epsilon = 0.0007000000000938176, rewards =  -38860
episode = 9993, epsilon = 0.0006000000000938176, rewards =  -33860
episode = 9994, epsilon = 0.0005000000000938175, rewards =  -62025
episode = 9995, epsilon = 0.0004000000000938175, rewards =  -34979
episode = 9996, epsilon = 0.0003000000000938176, rewards =  -35564
episode = 9997, epsilon = 0.0002000000000938176, rewards =  -35623
episode = 9998, epsilon = 0.0001000000000938176, rewards =  -31513
episode = 9999, epsilon = 9.381755897326649e-14, rewards =  -35037
```

It's clear that the larger number of states gives more rewards.

After, we (`https://github.com/duoduocai-dot/csc498-project/blob/main/tabular_Q_learning.py#L37`) just create a dictionary to store the policy and Q-values, with every possible state using the schema above.

3.1.1 Tabular Q-Learning

For tabular Q-Learning, now with a table of all possible states, we can just apply the Q-Learning epsilon greedy algorithm. Where the Q-Learning step:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma max_a Q(s_{t+1}, a) - Q(s_t, a_t)) \tag{1}$$

This exact Q-Learning update can be found here. Where we get the Q-value at each action for the next state, and plug in the max Q-value for the next state into the equation.

The other important aspect of Q-Learning is the epsilon-greedy exploration. We first initialize our epsilon in the class, then it is updated after every episode. The policy is updated for every state inside the q_learning function using the same epsilon-greedy approach.
For the epsilon decay, to increase exploitation rather than exploration, instead of the usual $\epsilon = \epsilon/k$ approach, we used a $\epsilon = \epsilon + decay$ where decay is usually some negative number between 0 and 1.

3.1.2 Tabular Double Q-Learning

In tabular double Q-Learning, our algorithm is nearly the exact same as tabular Q-Learning, except we maintain two Q-value dictionaries and each one is updated with 0.5 probability.
Pseudocode for double Q-Learning:
Select a_t using epsilon greedy $\pi(s) = argmax_a Q_1(s_t, a) + Q_2(s_t, a)$
with 0.5 probability:

$$Q_1(s_t, a_t) \leftarrow Q_1(s_t, a_t) + \alpha(r_t + \gamma Q_1(s_{t+1}, argmax_a Q_2(s_{t+1}, a)) - Q_1(s_t, a_t)) \tag{2}$$

else:

$$Q_2(s_t, a_t) \leftarrow Q_2(s_t, a_t) + \alpha(r_t + \gamma Q_2(s_{t+1}, argmax_a Q_1(s_{t+1}, a)) - Q_2(s_t, a_t)) \quad (3)$$

3.1.3 Tabular Sarsa

Tabular SARSA, implementation is similar to the above two, discretization of state space and epsilon-greedy exploration are both implemented the same way. Except the Q-value update is done using a bootstrapped one-step look ahead, like in the algorithm:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha(r_t + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t)) \quad (4)$$

3.1.4 Training

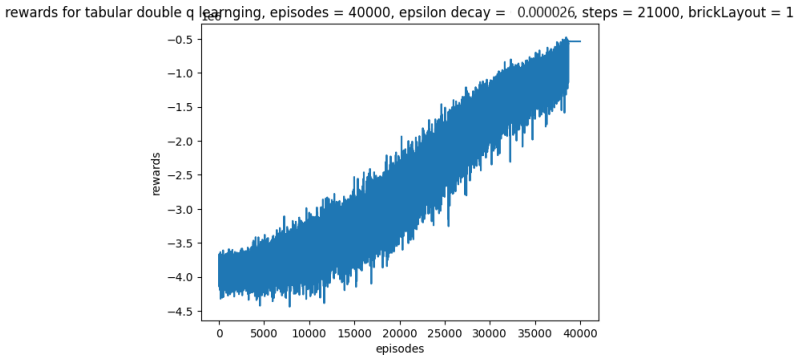
To train each of the algorithms, there is a training function which creates an instance of the algorithm then loops through a number of episodes collecting states, actions and rewards and using them for training. The code to run the training is commented out at the end of each file for SARSA, QL, and Double-QL

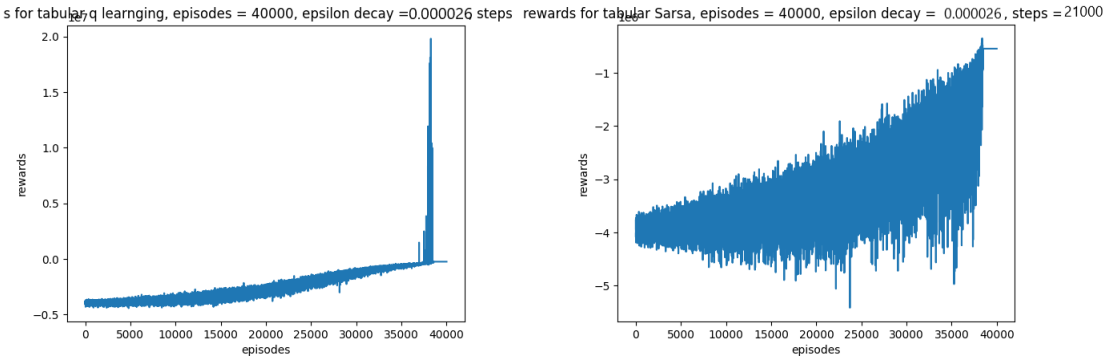
3.2 Tabular algorithms Analysis

3.2.1 Performance

All 3 tabular algorithms do achieve good performance and are able to play the game effectively.

Here are graphs for all 3 algorithms, it's clear that as episodes increase and epsilon grows smaller, all 3 algorithms achieve higher rewards. These graphs were made using the experiment2 function in tabular_experiments.py. All three algorithms were trained for 40000 episodes 21000 steps each, with a decay value of -0.000026 as specified in the experiment function. They were all trained on brick-layout 1 (the one with the spaces between bricks, check brick-layout section) The bottom left graph is Q-Learning, top is double Q-Learning, and bottom right is SARSA. Each algorithm took approximately 5-6 hours to train with the above episodes and steps.

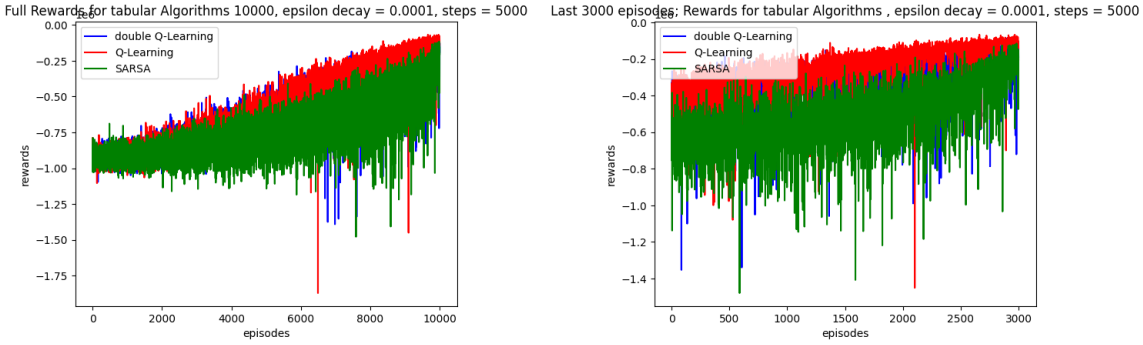




3.2.2 Comparing Tabular Algorithms

Here is a direct comparison of all 3 algorithms trained over 10000 episodes for 5000 steps per. It's clear from the pictures that Q-Learning and double Q-Learning outpreform SARSA.

Rewards Comparison of all 3 tabular algorithms and the last 3000 episodes comparison:



3.2.3 Parameter and Hyperparameter Choice

In the tabular algorithms there were many parameters that we used: epsilon and decay-value, episodes, step size, learning rate (α), discount (γ).

The choice of epsilon was simply just 1. We wanted lots of exploration in the beginning, for the agent to learn the environment. The epsilon decay was implemented such that: $\epsilon = \epsilon + decay$. The reason for this is because we wanted a linear decrease of epsilon to

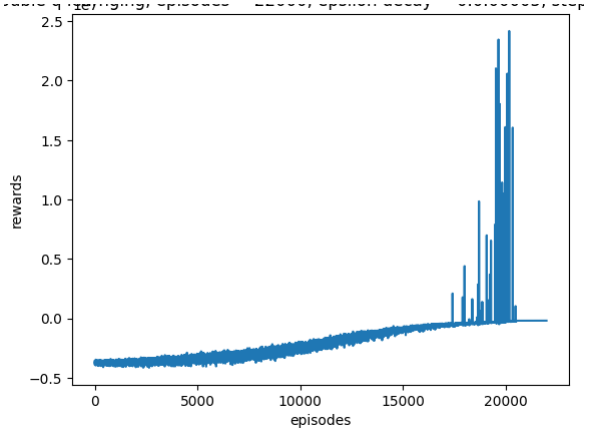
account for lots of exploration.

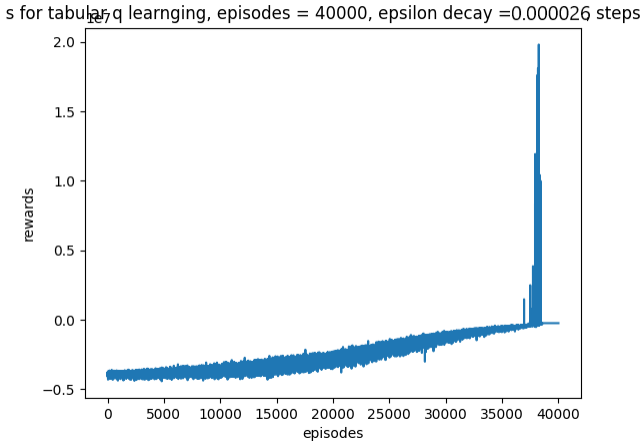
Our choice of step size to fully complete the game is 20000. The reason for the large step size is that the game overall takes a long time to complete. For example, this video example of a double Q-Learning agent playing the game takes atleast 30000 steps.

Our choice of γ was 0.9 because we wanted the agent to count future states heavily because it takes many steps for the agent to win the game, and we wanted to account for this with our discount.

3.2.4 Q-Learning maximization problems

We had maximization bias occur in some training sessions for Q-Learning:





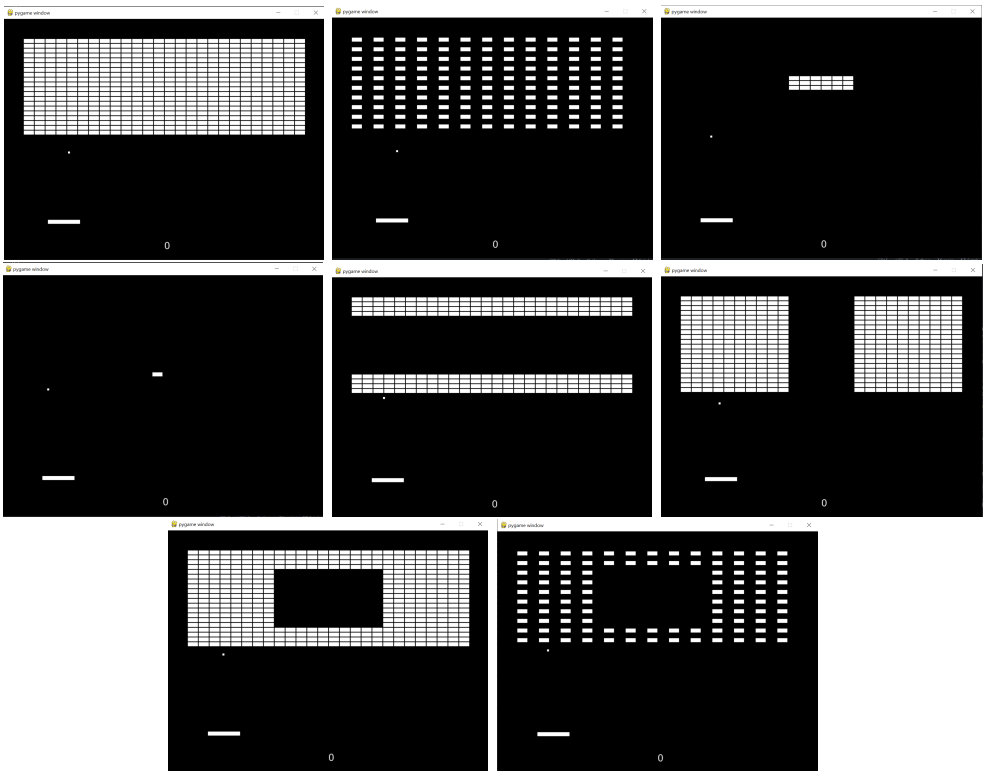
This is an example video of the agent playing the game, from the first graph. As it is seen from the end of the video, the agent gets stuck in an infinite loop of bouncing the ball in the same pattern which happens to avoid the blocks. From the graph, it is clear that the agent was able to win the game in some episodes (from 17000-22000), but after, the rewards converged. What ended up happening is that at some point in an episode the agent picks an

action that gives it a higher reward now, but not in the future. One reason for this is because the agent is essentially just trying to get as close to the ball as possible, from our reward model, we don't reward it when the ball hits a brick, and their is no brick representation in the state, so it's a partially observed state. So the agent is trying to center itself with the ball, but that doesn't guarantee that it will hit the ball in such a way that a brick will break.

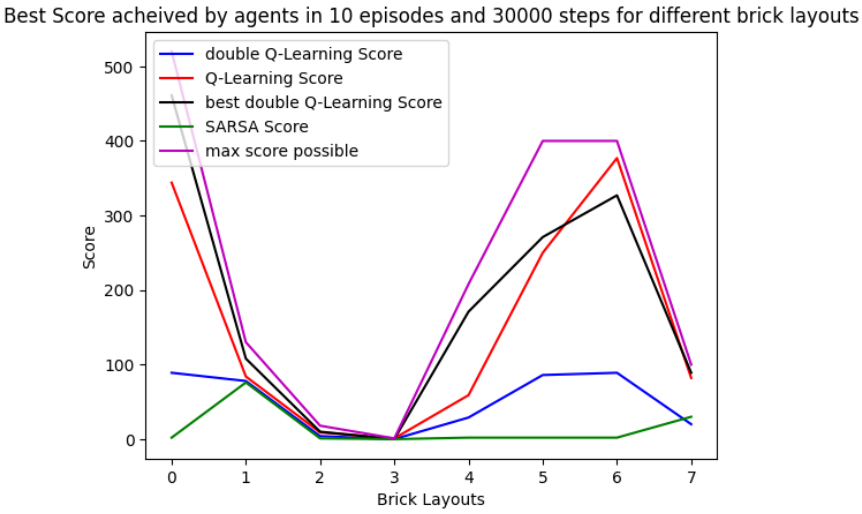
To fix this, we can add a more complex form of exploration, such that the agent can explore more when it gets close to the end or gets stuck in a loop of avoid bricks. Instead of just taking a max action.
Or we can change our entire environment to go from a partially observed MDP to a fully observed one, modelling brick-layout, score, ball location/speed, paddle location, etc. But for this, the algorithms also get more complex, we will need to utilize Neural Networks to handle the full states.
Another possible fix is to alter reward mechanics such that hitting a brick awards rewards. The reason we didn't do this initially is because the ball hitting is something that happens so much later after the paddle hits the ball that it was harming our training in the initial stages. I.e, the agent would get random rewards, but wouldn't be able to recreate it.

3.2.5 Generalization

Using the same agents trained in 3.2.1 section (all the algorithms trained on the same number of episodes and steps), we made generalization tests. In our environment we inbuilt several brick-layouts that the game can play on. These are:



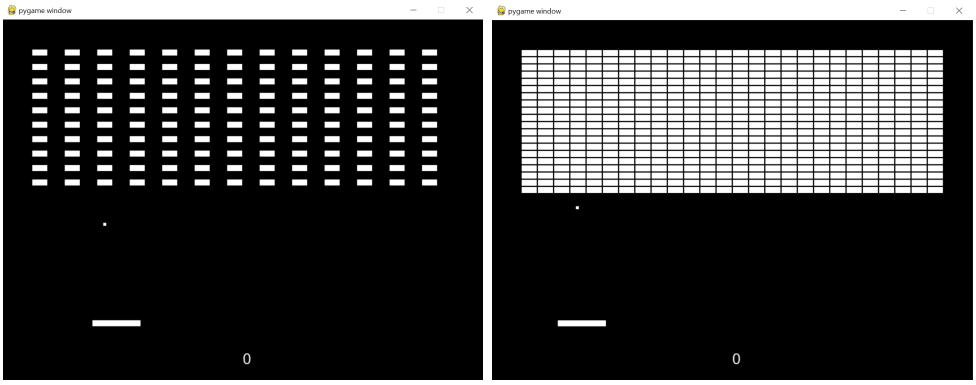
The experiment we made to test generalization is here. Essentially what it's doing is getting the trained agents from all 3 algorithms and running them across all layouts and measuring their score. Those algorithms were trained on layout1 (second layout in the top row). And along with them we included one more trained double Q-Learning agent which was trained for 100,000 episodes, and graphed the results. On the graph is also the max possible score achievable per layout as a reference to how well the algorithm does.



We can see both the Q-Learning and the best double Q-Learning algorithm do very well in generalizing across different layouts, both their scores are close the the maximum possible score.

3.2.6 Which Layout is best to train on?

We think that the layout best to train on is brick-layout number 1 (left). It is better than brick-layout 0 (right) because it allows for the ball to go in between bricks in a much earlier part of the episode than layout 0 allows. Thus the agent is able to learn more variations of ball locations and velocities.



Talk about

- epsilon choice and decay choice, step and episode size
- preformance of each algorithm
- maximization problem with Q-Learning, and how altering reward schema can fix it.
- How the above can be fixed with a different epsilon greedy approach (epsilon goes down to 0, then up to 1, then back down, repeats for n times, when it ends its at 0). This approach is to make sure there is enough exploration in the later regions of the game.
- comparing algorithms in generalized tests, also talk about generalized brick layouts
- Talk about which bricklayout is best to train on to maximize most generalization of agent (bricklayout1)

3.3 Policy Gradient

talk about

- problems with original reward schema and how because of policy gradient we altered it
- gradients getting trapped in local mins/maxes
- fixes for this which can include lowering learning rate, using momentum in gradient or using soft-actor-critic, or using exploration
- talk about the epsilon-greedy exploration currently implemented

3.4 Deep Recurrent Q-Network

The deep recurrent Q-network has most of the ideas from the paper ..., to calulate the target function, we utilize a gated recurrent unit with one layer. Architecture: unidirectional, input size: 6 (observation space), one hidden layer of size 10, output size 3 (action space). In the forward pass, the computed value is then passed into a linear model. In the experience replay buffer, we sample sequences instead of single points.
The resaon we use GRU:

- Given that the problem is relatively simple, using LSTM is inefficient.
- The forget gate of LSTM is not useful in our case, because we don't need to skip any weak past frame and reuse them in later stages.