UNIVERSITÀ DEGLI STUDI DI VERONA

DIPARTIMENTO DI INFORMATICA

Final project for the "fundamentals of Artificial Intelligence" course:

CartPole-v1 trained with DQN using CNN

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Chapter 1

Problem definition:

A pole is attached by an un-actuated joint to a cart, which moves along a frictionless track. The system is controlled by applying a force of +1 or -1 to the cart. The pendulum starts upright, and the goal is to prevent it from falling over. A reward of +1 is provided for every timestep that the pole remains upright. The episode ends when the pole is more than 15 degrees from vertical, or the cart moves more than 2.4 units from the center.
CartPole-v1 defines "solving" as getting average reward of 195.0 over 100 consecutive trials.

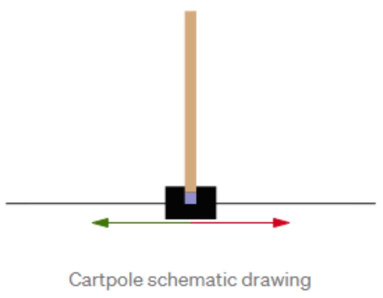


Figure 1.1: CartPole-v1 environment from OpenAI gym

This work is based on OpenAI's gym[1][2], a toolkit for developing and comparing reinforcement learning algorithms.
In this particular environment the observation space (possible state values) are four and the action space (possible actions that can be performed) are two. The table presented here below summarize the problem statement:

Observation			
Num	Observation	Min	Max
0	Cart Position	-4.8	4.8
1	Cart Velocity	-∞	+∞
2	Pole Angle	-24°	+24°
3	Pole Angular speed	-∞	+∞

Action	
Num	Action
0	Push cart to the left
1	Push cart to the right

1.1 Assigned task

In this work the first task to solve was solving CartPole-v1 with the DQN algorithm[3], i.e as mentioned before, get an average reward of 195.0 over 100 consecutive trials, using a normal deep neural network. Here we have the observation state that could be represented with few features (4) but we have continuous states. We use Reinforcement Learning in particular DRL because we can not have a table Q(s,a) for each possible state since the variables defined in the table above has real domain.

The second task assigned was to solve CartPole-v1 using always the DQN algorithm but this time using Convolutional Neural Networks (CNN).

Chapter 2

Why CNN?

2.1 What is convolution? (briefly)

Convolutional operation in digital signal processing is also called filtering a signal with a particular kernel, which is a vector or a matrix. Generally, the kernel is also called a filter. This latter computes the local averages by averaging the values within a window. If we see an example with an image and a filter 3x3, the convolution returns something like this:

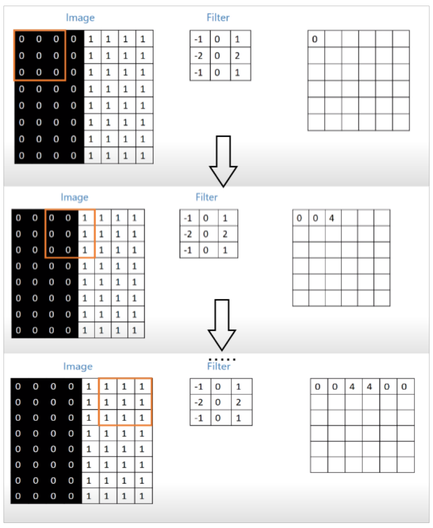


Figure 2.1: Convolution operation

In the example, we see the first part of a convolution of an 8x8 image with a 3x3 kernel or filter. The operation involves the overlay of the kernel on the image, multiply the elements, sum the products, and move to the next tile. This specific kernel used in the example is an edge detector that detects the vertical edges of images. We use CNN to have a model that learns parameters from data and discovers what kind of feature extractors would be useful to accomplish a task.
In particular, we need and use CNN because let us suppose to have a 300x300 rgb image, and we want to use a deep neural network with images as input. In this situation, all the hidden units of the network would be connected to all pixels in input and we would have 270,000 weights for a single neuron!
If we build a model that has many fully connected units at every layer the model would be slow and prone to overfitting.
To solve this problem we can connect each neuron to only a region of the input/image, in other words, we could make a convolution of the image. A layer that consists of convolutional units like these presented before is called a convolutional layer. The parameters learned by each unit in a convolutional layer can be thought of as a filter and the output of these units are simply the filtered versions of their inputs.
One of the main advantages of having these CNNs is the abstraction level that you can have in each level, that is, each level extracts a certain type of image features, and therefore by changing the various kernels/filters you can extract various details of the image.

Chapter 3

Implementation and results

In this chapter, I will present the implementation with CNN done.

3.1 Model

Resolving CartPole using images involves using the
$env.render(mode = \text{'rgb\_array'})$ function to have a rendered frame image for each step of the episode. Obviously, retrieving every single frame is computationally heavy and takes a long time, which is one of the reasons why the CNNs take longer to solve a task than using the input directly with a DNN. Cartpole gym environment outputs 600x400 RGB arrays (600x400x3). That was way too many pixels with such simple task, more than I needed, so I converted the output to grayscale and I downsized it. The result was something like this:

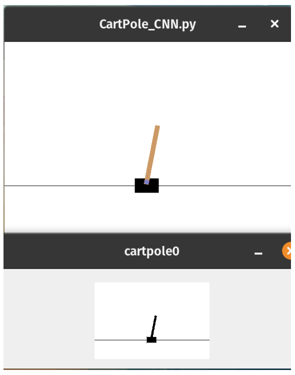


Figure 3.1: rendered frame image grayscaled and downsized

In order to derive both the direction, velocity and acceleration of the moving object, I kept last 4 frames for each step, so my input for the CNN was a numpy array of (240x160x4). For building the model I used Tensorflow and in particular Keras. This latter is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library.

3.2 Architecture

The input to the neural network consisted of 160x240x4 images. After the input layer there were three 2D convolutional layers with kernel that started from 5x5 and became 3x3 in the last layer of Conv2D with stride 3x3, 2x2 and 1x1 in the last 2D convolutional layer.
The Stride basically told me how much shift the window during convolution. As mentioned above one of the main advantages of having these CNNs is the level of abstraction that you can have in each level, that is, each level extracts a certain type of image feature.
I used relu activation function for each layer both Conv2D and Dense. The final hidden layer was fully connected "Flatten" units and I obtained as output of this Flatten layer 52992 nodes which were the inputs for the following four Dense levels of the neural network. I used four levels compared to a possible normal DQN implementation using only DNN that could require only two hidden layer, because here I started from a very large input and it seemed like too drastic to reduce immediately to two layers of 128 and 64 for example.

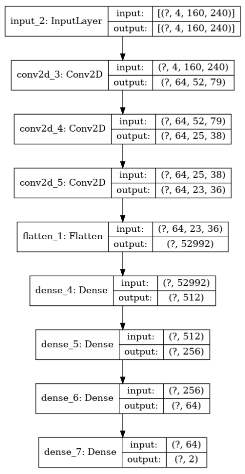


Figure 3.2: Model architecture

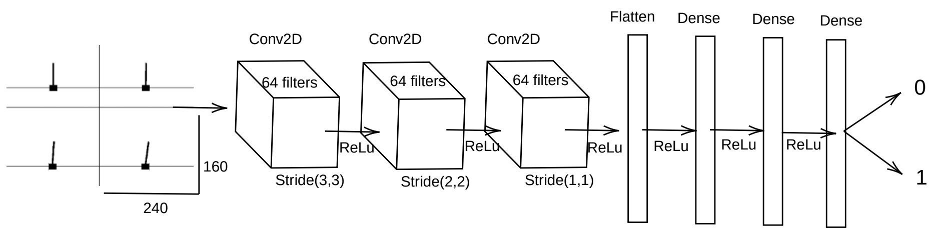
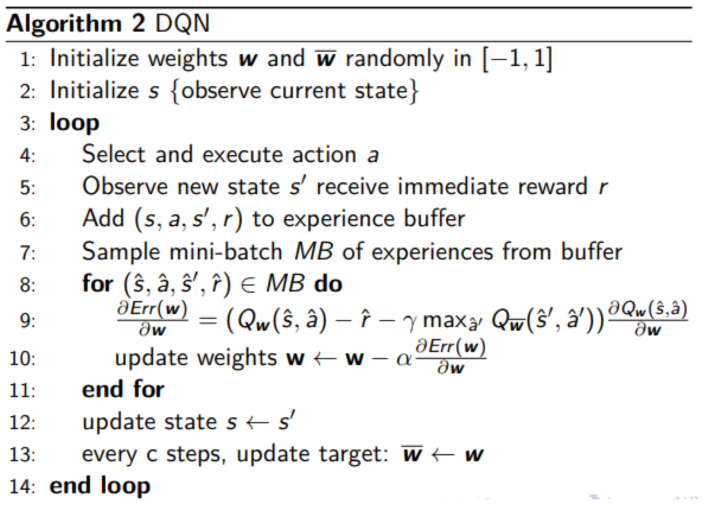


Figure 3.3: Model architecture

The algorithm used is the classic DQN[3]:



Algorithm 2 DQN

```
1: Initialize weights $\boldsymbol{w}$ and $\overline{\boldsymbol{w}}$ randomly in $[-1, 1]$
2: Initialize $s$ {observe current state}
3: loop
4:     Select and execute action $a$
5:     Observe new state $s'$ receive immediate reward $r$
6:     Add $(s, a, s', r)$ to experience buffer
7:     Sample mini-batch $MB$ of experiences from buffer
8:     for $(\hat{s}, \hat{a}, \hat{s}', \hat{r}) \in MB$ do
9:         $\frac{\partial Err(\boldsymbol{w})}{\partial \boldsymbol{w}} = (Q_{\boldsymbol{w}}(\hat{s}, \hat{a}) - \hat{r} - \gamma \max_{\hat{a}'} Q_{\overline{\boldsymbol{w}}}(\hat{s}', \hat{a}')) \frac{\partial Q_{\boldsymbol{w}}(\hat{s}, \hat{a})}{\partial \boldsymbol{w}}$
10:        update weights $\mathbf{w} \leftarrow \mathbf{w} - \alpha \frac{\partial Err(\boldsymbol{w})}{\partial \boldsymbol{w}}$
11:    end for
12:    update state $s \leftarrow s'$
13:    every c steps, update target: $\overline{\boldsymbol{w}} \leftarrow \boldsymbol{w}$
14: end loop
```

The results are presented in the next page.

3.3 Results:

All the plot shown below are the average reward over 100 consecutive trials. The first result presented is the solution of CartPole-v1 with DNN using DQN algorithm:

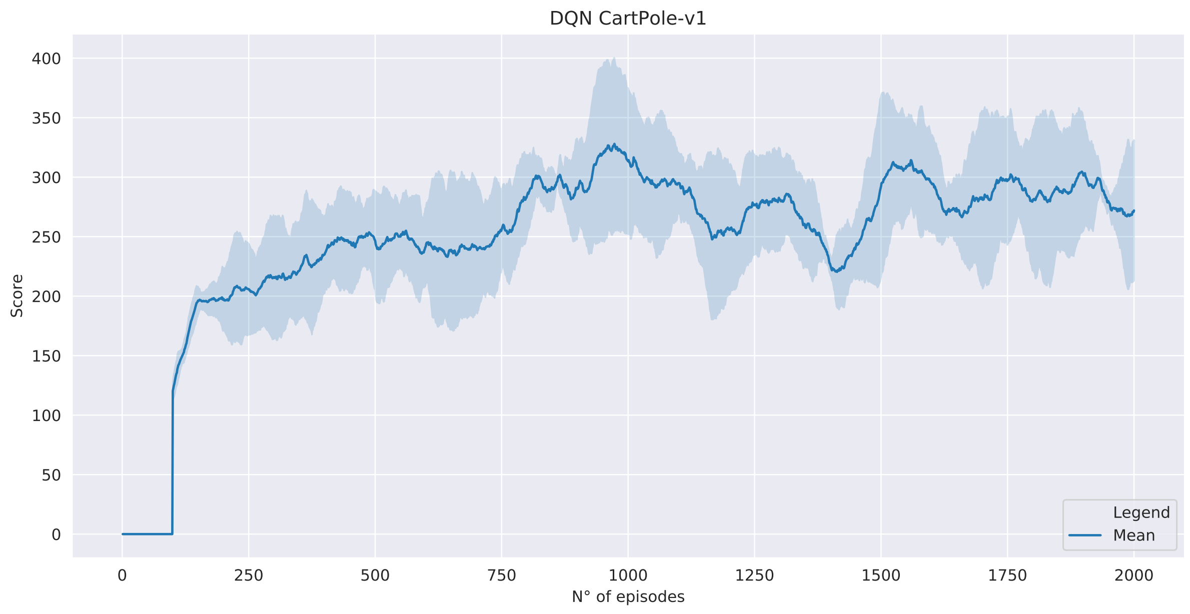


Figure 3.4: CartPole-v1 using DQN algortithm

As we can see from the plot starting from episode 150 more or less the CartPole-v1 is "solved" since it had an average reward of 195.0 or greater over 100 consecutive trials.

The second result presented is the solution of CartPole-v1 with CNN using DQN algorithm:

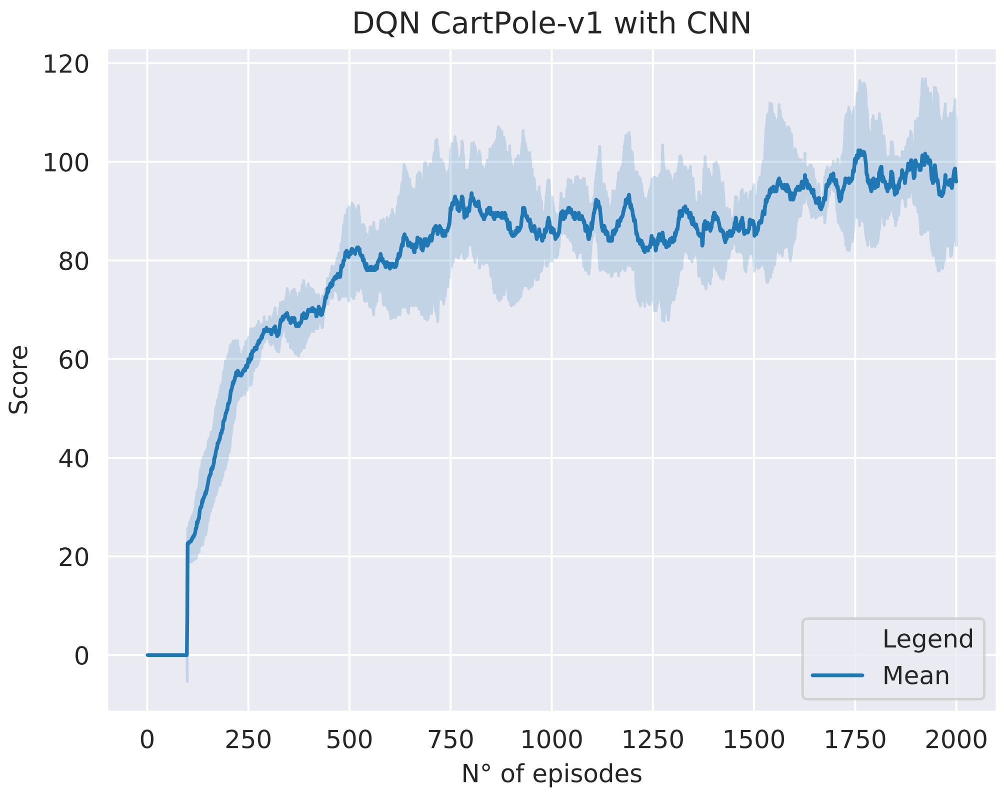


Figure 3.5: CartPole-v1 using CNN

Making a comparison between the two plots, with the same number of episodes completed, we note that the use of images and in particular CNN to solve the task requires more time to consider the CartPole task solved. However, we can see how the average is constantly increasing, so I speculate that with other 2000 episodes the task can be solved also with CNN.

Bibliography

[1] `https://gym.openai.com/docs/`

[2] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba, "Openai gym," arXiv preprint arXiv:1606.01540, 2016

[3] Human-level control through deep reinforcement learning (V. Mnih et al., Nature 2015)