Deep Q-Network Demo

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Basic Implementation

Code

Manual Implementation

– The code for this project is available at: `https://github.com/rish987/Reinforcement-Learning/blob/master/demos/deep_q_network/code/deep_q_network.py`.

Keras Implementation

– The code for this project is available at: `https://github.com/rish987/Reinforcement-Learning/blob/master/demos/deep_q_network/code/deep_q_network_keras.py`.

Implementation Details

– Unlike the Atari gameplay environment described by Mnih et. al., the pole-cart environment is not perceptually aliased. That is, the current observation of the state is theoretically all that is needed to determine an optimal value. Therefore, the current state can be equated with the current observation, without taking into account past observations and actions.

– Because the observation space of the Atari gameplay environment is much larger than the pole-cart environment, it should suffice to use a smaller ANN model.

– Because the observation space of the pole-cart environment is small and not spatially correlated, it is not helpful to use a convolutional neural network.

Manual Implementation

– The model is a simple vanilla neural network with one hidden layer:

  – Let M be the number of nodes in the hidden layer.
  – Let K be the number of output nodes (i.e., number of actions).
  – Let $\sigma(x)$ be the sigmoid activation function $\frac{1}{1+e^{-x}}$.

- The hidden layer is calculated as:

$$Z_m = \sigma(\alpha_{0m}^T + \alpha_m^T x(s)), m = 1, \ldots, M$$

- The output layer is calculated as:

$$\hat{q}(s, a_i; \theta) = \beta_{0i} + \beta_i^T Z, i = 1, \ldots, K$$

- Solving for the gradient of the sample error:

$$\nabla_\theta J_t(\theta) = -2(y_t - \hat{q}(s_t, a_t, \theta))\nabla_\theta \hat{q}(s_t, a_t, \theta)$$

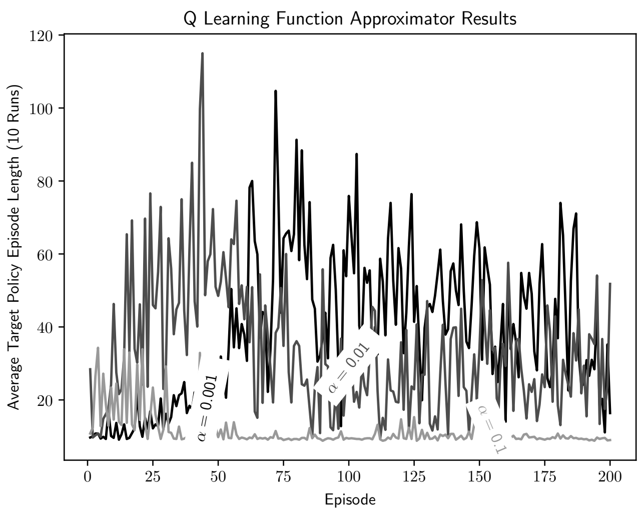
$$\frac{d}{d\beta_{jk}}\hat{q}(s_t, a_t, \theta) = \begin{cases} 0 & k \neq a_t \\ \begin{cases} 1 & j = 0 \\ \sigma(\alpha_{0j}^T + \alpha_j^T x(s_t)) & j > 0 \end{cases} & k = a_t \end{cases}, k = 1, \ldots, K$$

$$\frac{d}{d\alpha_{im}}\hat{q}(s_t, a_t, \theta) = \beta_{mk}\sigma'(\alpha_{0m}^T + \alpha_m^T x(s_t)) \begin{cases} 1 & i = 0 \\ x(s_t)_i & i > 0 \end{cases}$$

- A decaying ϵ was used, which started at 1.0 and decayed to a minimum value of 0.01.
- A constant decay rate was used for the learning rate α. Keras Implementation
  - The size of the model seemed to significantly affect the performance of the Keras ANN. I found that a model that yielded good (though perhaps not optimal) results contained two hidden layers of 24 nodes each, with ReLU activation functions.
  - Other than replacing the model and outsourcing gradient calculation, the general algorithmic framework remained the same.

Results

Manual Implementation



– The results for different α can be summarized as follows:

  – The largest α learned initially, but worsened and failed to find a policy that was capable of passing the episode at all. This suggests that, in starting with a larger α, it could be useful to decay by a larger factor.

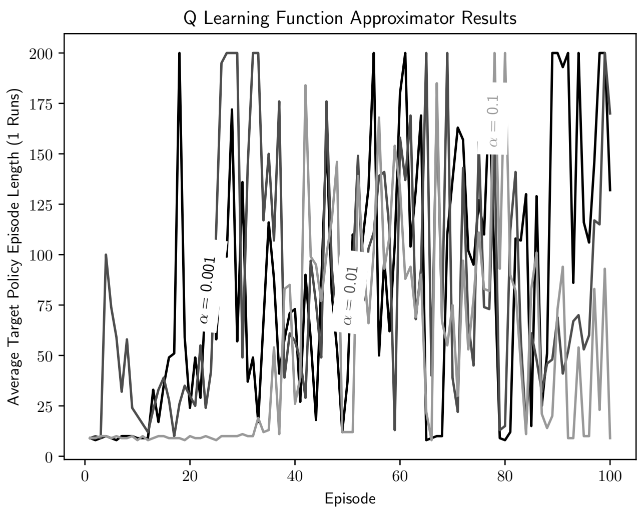
  – The middle α learned very well initially, but worsened and failed to find a policy that was capable of consistently passing the episode. This also suggests that, in starting with a larger α, it could be useful to decay by a larger factor.

  – The small α learned slowly, but eventually leveled off at a better policy than those of the other αs. This may mean that the decay rate was too large relative to this α, causing it to cease improving after α became negligibly small.

– These results suggest that this learner is feasable, and in order to improve this learner, it is necessary to more carefully control how α decays over time. It may also be useful to increase the number of hidden layers in the model.

– To verify that this was the case, I move on to replacing my manual implementation with a Keras implementation that handles training on its own and with which I can easily change the ANN parameters.

Keras Implementation



Note: Because Keras took significantly longer to run, I didn't collect enough data to average, which explains the noise. However, I observed that the smallest learning rate ($\alpha = 0.001$) consistently scored > 150 on subsequent runs.

– The results for different α can be summarized as follows:

  – The largest α performed poorly initially, but learned a policy that generally performed worse than the other two αs.

  - The middle α Learned quickly, and performed averagely compared to the other two αs.
  - The smallest α learned quickly, and performed relatively well, converging to an almost optimal policy.

- This clearly outperforms my manual implementation, but when I reduced the model to approximately the size of my manually constructed model, it performed similarly. This suggests that the size of the neural network and intelligent control of the learning rate can significantly affect the performance of the algorithm.