Computational Assignment 1

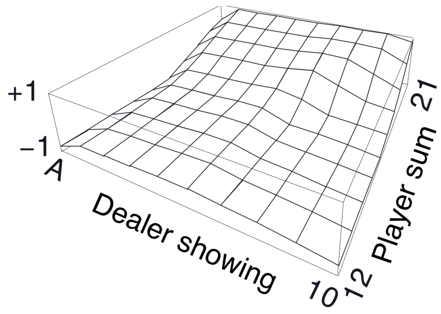
Easy 21

The goal of this assignment is to apply reinforcement learning methods to a simple card game that we call *Easy21*. This exercise is similar to the Blackjack example in Sutton and Barto 5.3 ? please note, however, that the rules of the card game are different and non-standard.

- The game is played with an infinite deck of cards (i.e. cards are sampled with replacement)
- Each draw from the deck results in a value between 1 and 10 (uniformly distributed) with a colour of red (probability 1/3) or black (probability 2/3).
- There are no aces or picture (face) cards in this game
- At the start of the game both the player and the dealer draw one black card (fully observed)
- Each turn the player may either stick or hit
- If the player hits then she draws another card from the deck
- If the player sticks she receives no further cards
- The values of the player's cards are added (black cards) or subtracted (red cards)
- If the player's sum exceeds 21, or becomes less than 1, then she "goes bust" and loses the game (reward -1)
- If the player sticks then the dealer starts taking turns. The dealer always sticks on any sum of 17 or greater, and hits otherwise. If the dealer goes bust, then the player wins; otherwise, the outcome - win (reward $+1$), lose (reward -1), or draw (reward 0) - is the player with the largest sum.

Implementation of Easy 21 (20 marks

You should write an environment that implements the game *Easy21*. Specifically, write a function, named step, which takes as input a state s (dealer's firstcard $1-10$ and the player's sum $1-21$), and an action a (hit or stick), and returns a sample of the next state s' (which may be terminal if the game is finished) and reward r. We will be using this environment for model-free reinforcement learning, and you should not explicitly represent the transition matrix for the MDP. There is no discounting ($\gamma = 1$). You should treat the dealer's moves as part of the environment, i.e. calling step with a stick action will play out the dealer's cards and return the final reward and terminal state.



Monte-Carlo Control in Easy21 (40 marks)

Apply Monte-Carlo control to *Easy21*. Initialise the value function to zero. Use a time-varying scalar step-size of $\alpha_t = 1/N(s_t, a_t)$ and an ϵ-greedy exploration strategy with $\epsilon_t = N_0/(N_0 + N(s_t))$, where $N_0 = 100$ is a constant. $N(s)$ is the number of times that state s has been visited, and $N(s, a)$ is the number of times that action a has been selected from state s. Feel free to choose an alternative value for N_0, if it helps producing better results. Plot the optimal value function $V^*(s) = \max_a Q^*(s, a)$ using similar axes to the following figure taken from Sutton and Barto's Blackjack example.

TD Learning in Easy21 (40 marks)

Implement Sarsa(λ) in 21s. Initialise the value function to zero. Use the same step-size and exploration schedules as in the previous section. Run the algorithm with parameter values $\lambda \in \{0, 0.1, 0.2, \ldots, 1\}$. Stop each run after 1000 episodes and report the mean-squared error

$$\sum_{s,a} \big(Q(s, a) - Q^*(s, a)\big)^2$$

over all states s and actions a, comparing the true values $Q^*(s, a)$ computed in the previous section with the estimated values $Q(s, a)$ computed by Sarsa. Plot the mean-squared error against λ. For $\lambda = 0$ and $\lambda = 1$ only plot the learning curve of mean-squared error against episode number.

Submission

- You should submit a single pdf document containing your plots and interpretations, and a single archive containing all your source code.
- Please organize your source code so that it is easy to follow and apparent how to run your solutions to the assignment's questions, e.g. by naming the relevant files and/or functions question2, question3, etc.
- Submit your submission in Moodle.
- The deadline for the assignment is 8/10/2018.
- This assignment should be completed *individually*.