## CM20252 & CM50263 Artificial Intelligence

## Coursework: Programming 2

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**Date set:** 9 April 2018
**Date due:** 23 April 2018, 11:00 am
**Total marks:** 100

CM20252 students: This coursework will determine 20% of your mark for the unit.
CM50263 students: This coursework will determine 16% of your mark for the unit.

**Where to submit:** CM20252 Moodle page
**What to submit:** Completed Jupyter notebook (.ipynb file)

You will be given a Jupyter notebook to work with. You must follow the instructions on this notebook and submit this particular notebook. Otherwise you will receive 0 marks.

**Late submissions:** We will follow the university policy on late submissions.

Coursework submitted after the deadline will receive a maximum mark of 40 (out of 100).
Coursework submitted after five working days will receive a mark of zero.

**Feedback:** Within two weeks of the submission deadline, your Jupyter file will be returned to you (via Moodle), showing the marks you received from each part of the coursework. You can get additional feedback from the unit leader or one of the tutors via appointment.

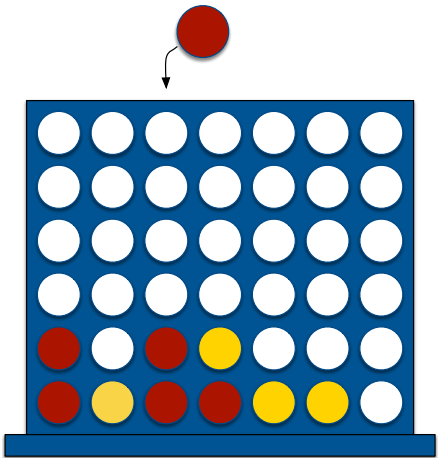
You are required to work individually. You are welcome to discuss ideas with others but you must design your own implementation and write your own code.

This coursework will be marked anonymously. Please do not include any identifying information on the files you submit.

Do not plagiarise. Plagiarism is a serious academic offence. For details on what it is and how to avoid it, please visit the following webpage:
http://www.bath.ac.uk/library/help/infoguides/plagiarism.html

You will work on Connect Four, a game that some of you may have seen before in other units. This time it will be mainly about Q-learning. Connect Four is a small but relatively interesting game to try reinforcement learning on.
The coursework has three parts. You have the possibility of obtaining 70 marks by completing only the first part. You are, of course, encouraged to complete all three parts: this will help you in developing a deep understanding of some of the concepts discussed in the class. Please note that the distribution of marks do not reflect the educational value of each part of the coursework.
For most of you, I expect that this coursework will require a longer time to complete than Coursework 1. I expect that it will also take longer than Coursework 3, which you will receive in two weeks.

**What you need to do**



*Connect Four* is a two-player zero-sum game played on a vertical grid, as shown in the figure. Each player is given disks of a particular colour. The players take turns dropping one of their disks from above the grid, into one of the columns. The piece falls straight down, occupying the lowest empty slot within the column. The objective of the game is to be the first to form a horizontal, vertical, or diagonal line of four discs. If the grid fills up before either player achieves the objective, the game is a draw.

The original game is played on a 6×7 grid, as shown in the figure. The first player begins the game by dropping one of her discs into the centre column. You will work on a simpler version of the game, called *Connect Three*, where a player needs to connect only three pieces in order to win the game. In addition, you will use a grid smaller in size than the standard grid. Exact details are provided in the Jupyter file.

**Part 1 (70 marks)**

Apply Q-learning to learn an optimal policy when playing against an opponent who chooses moves uniformly at random[1]. Compare the performance of your policy to the performance of random play.

You may notice in the reference textbook (Sutton & Barto) that Q-learning has more complex versions than the one we covered in the lectures. You are limited to using the version we covered.

Use a reward function that assigns +1 for a win, –1 for a loss, and 0 for a draw. Use initial Q-values of zero. Choices of parameters $\alpha$ (step size) and $\varepsilon$ are up to you. Experiment with different values to gain an understanding of how these parameters impact learning. You may change $\alpha$ and $\varepsilon$ over time. It is also up to you to determine any other experimental parameters you will need, for example, how many games the agent should learn from.

You will be given some code that implements the game dynamics. This code is provided to you as a starting point. You may want to modify the existing code to suit your needs. You will need to write additional functions. You are also free to write your own code from scratch but please keep in mind that you are responsible for implementing the game dynamics accurately. You will notice that the existing code helps with the implementation of the game but not with the machine learning component of the coursework. This is intentional. You are expected to write your own code for the entirety of the agent's interaction with its environment in order to learn how it can best play this game.

[1] All columns that are not already full have equal probability of being selected.

Marking guideline:

In order to obtain full marks for Part 1, you need to demonstrate an excellent understanding of Q-learning, with efficient learning of the optimal policy. Note that a more *efficient* method needs fewer observations to reach a certain level of play.

If you can demonstrate eventual learning of the optimal policy (but not necessarily efficiently), you will receive 60 marks or above, depending on how efficiently your agent learns.

If you can demonstrate some amount of learning, you will receive 40 marks or above, depending on how well your policy performs.

Your code is expected to be well organised and readable. Otherwise, your marks may be lower than indicated in this guideline.

**Part 2 (20 marks)**

(A) Using adversarial search, compute the optimal policy assuming an optimal opponent. We will call this the *Minimax Policy*. You will receive higher marks for more efficient search that examines fewer branches of the game tree. (15 marks)

(B) Against an opponent who chooses moves uniformly at random, compare the performance of the Minimax Policy to the performance of the policy computed in Part 1. Which policy is better? Why? (5 marks)

**Part 3 (10 marks)**

Using an algorithm similar to Minimax, compute the optimal play against an opponent that selects moves uniformly at random. The opponent always starts first.

Against this random opponent, compare the performance of your algorithm to the performance of the agents you developed in Part 1 (Q-learning) and Part 2 (Minimax).

You may find it useful to read Section 5.5 of the textbook (Russell & Norvig), which explains how to adapt Minimax to stochastic games.

For all parts of this coursework, additional details are provided in the Jupyter file.
**You must follow the instructions in the Jupyter file precisely.**

Two weeks of lab sessions are allocated for you to work on this coursework. Our tutors will be available during these lab sessions to answer your questions and to help you in any way they can. You can also consult the unit leader in her office hours, during the lectures, or by appointment.