## Problem Set VII: Value & Policy Iteration

**Aim** The purpose of this workshop is to help you get a better understanding of MDPs, value iteration, and policy iteration.

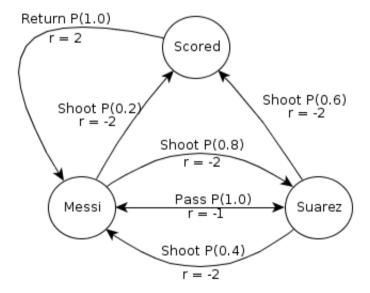
Consider two football-playing robots: Messi and Suarez.

They play a simple two-player cooperate game of football, and you need to write a controller for them. Each player can pass the ball or can shoot at goal.

The football game can be modelled as a discounted-reward MDP with three states: *Messi*, *Suarez* (denoting who has the ball), and *Scored* (denoting that a goal has been scored); and the following action descriptions:

- If Messi shoots, he has 0.2 chance of scoring a goal and a 0.8 chance of the ball going to Suarez. Shooting towards the goal incurs a cost of 2 (or a reward of -2).
- If Suarez shoots, he has 0.6 chance of scoring a goal and a 0.4 chance of the ball going to Messi. Shooting towards the goal incurs a cost of 2 (or a reward of -2).
- If either player passes, the ball will reach its intended target with a probability of 1.0. Passing the ball incurs a cost 1 (or a reward of -1).
- If a goal is scored, the only action is to return the ball to Messi, which has a probability of 1.0 and has a reward of 2. Thus the reward for scoring is modelled by giving a reward of 2 when leaving the goal state.

The following diagram shows the transition probabilities and rewards:



## Tasks

1. Assume that we have calculated the following non-optimal value function V for this problem using value iteration with  $\gamma = 1.0$ , after iteration 2 we arrive at the following:

Iteration		0	1	2	3
V(Messi)	=	0.0	-1.0	-2.0	
V(Suarez)	=	0.0	-1.0	-1.2	
V(Scored)	=	0.0	2.0	1.0	

If Messi has the ball (the system is in the Messi state), what action should we choose to maximise our reward in the next state: pass or shoot? Assume we are using the values for V after three iterations.

- 2. Complete the values of these states for iteration 3 using value iteration. Show your working.
- 3. Consider the following policy update table and policy evaluation table, with discount factor  $\gamma=0.8$  :

Iter	$Q^{\pi}(Messi, P)$	$Q^{\pi}(Messi, S)$	$Q^{\pi}(Suarez, P)$	$Q^{\pi}(Suarez, S)$	$Q^{\pi}(Scored)$
0	0	0	0	0	0
1					
2	-4.194	-5.465	-4.355	-3.993	-1.355

Apply two iterations of policy iteration. Finish both tables and show the working for the policy evaluation and policy update.

What is the policy after two iterations?

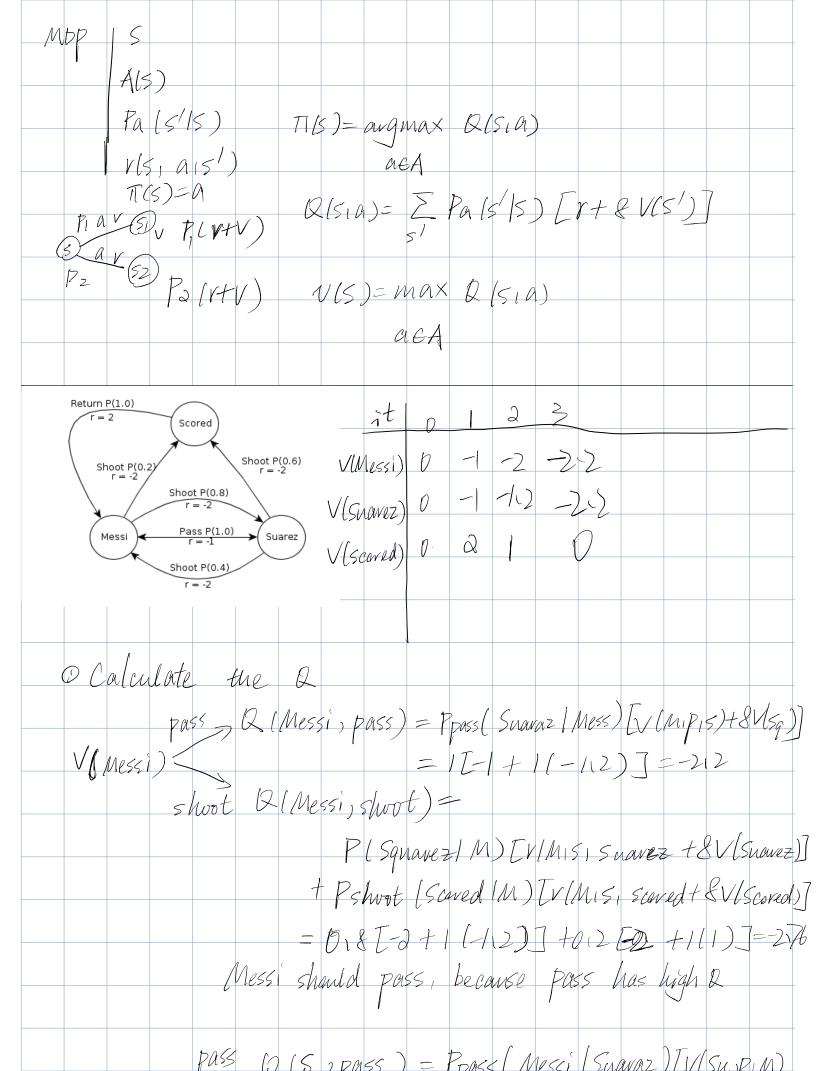
Iter	$\pi(Messi)$	$\pi(Suarez)$	$\pi(Scored)$
0	Pass	Pass	Return
1			Return
2			Return

## Additional Tasks for Personal Study

To improve your understanding of value iteration, try completing the first question of Project 3 at http://ai.berkeley.edu/reinforcement.html#Q1. You can download all the necessary files to complete this task.

Hints In order to help you complete the task during the workshop, here are some useful hints:

- 1. The functions that you need to change:
  - (a) \_init\_
  - (b) computeQValueFromValue
  - (c) compute Action From Value
- 2. The files you need to take a look:
  - (a) util.py (Counter())
  - (b) mdp.py (isTerminal(), getStates() ,getPossibleActions(), etc.)
  - (c) other files: (gridworld.py, learningAgent.py) not directly related
- 3. How to test your code:
  - (a) python autograder.py -q q1 (testing by autograde)
  - (b) python gridworld.py -a value -i 5 (result after 5 iteration)
  - (c) python gridworld.py -a value -i 100 -k 10 (how value iteration works)



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