Week 9: Temporal difference learning

COMP90054 – AI Planning for Autonomy

Key concepts

- Q-learning and SARSA
- On-policy vs off-policy learning

Model-based vs Model-free

- Model-based: Know the transition probability $P_a(s'|s)$ and reward function r(s, a, s')
  - E.g: Value Iteration
- Model-free: Don't know the transition probability and reward function
  - E.g: SARSA, Q-learning

Q-learning vs. SARSA

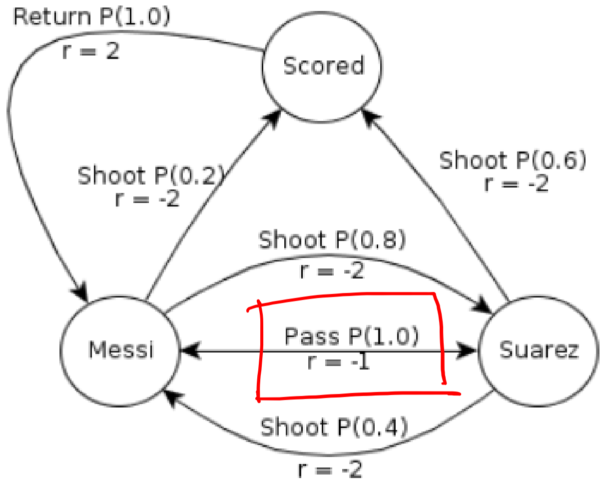
Q-learning (Off-policy)	SARSA (On-policy)
$Q(s,a) = Q(s,a) + \alpha[r + \gamma \boxed{\max_{a' \in A(s')} Q(s',a')} - Q(s,a)]$	$Q(s,a) = Q(s,a) + \alpha[r + \gamma \boxed{Q(s',\pi(s'))} - Q(s,a)]$
Update rule: Not update based on the policy. Update Q-function based on the assumption that the next action would be the action with the maximum Q. Optimistic: the greedy action will be chosen while in fact, the policy may choose an action other than the best	Update rule: Updated based on the policy. We know the action that it will execute next (whether it is best or not) when performing the update
• Learning from prior experience • The main advantage of off-policy approaches is that they can use samples from sources other than their own policy.	• Learning on the job • The main advantage of on-policy approaches is that they can learn optimal behaviour while operating in their environment.

Combine Q-learning + SARSA. (should not start with a random policy).

+ Use Q-learning to get a sample policy.
+ Use SARSA to optimise the policy.

Problem 2: Q-learning

The following diagram shows the transition probabilities and rewards:



Q-table

	Pass	Shoot	Return
Messi	-0.4	-0.8	-
Suarez	-0.7	-0.2	-
Scored	-	-	1.2

$Q(\text{Messi}, \text{pass}) = -0.4$

In the next step of the episode, from the state 'Suarez', Suarez passes the ball to Messi. Show the Q-learning update for this action using a discount factor $\gamma = 0.9$ and learning rate $\alpha = 0.4$

Note: Assume that this is a model-free problem, so the transition probabilities are not accessible to your algorithm.

$$Q(s,a) = Q(s,a) + \alpha[r + \gamma \boxed{\max_{a' \in A(s')} Q(s',a')} - Q(s,a)]$$

$$\underset{s}{\text{Suarez}} \xrightarrow[a]{\text{pass}} \underset{s'}{\text{Messi}}$$

$$Q(\text{Suarez}, \text{pass}) = Q(\text{Suarez}, \text{pass}) + \alpha[r + \gamma \max_{a' \in A(\text{Messi})} Q(\text{Messi}, a') - Q(\text{Suarez}, \text{pass})]$$

$$= -0.7 + 0.4[-1 + 0.9 \times (-0.4) - (-0.7)]$$

$$= -0.964$$

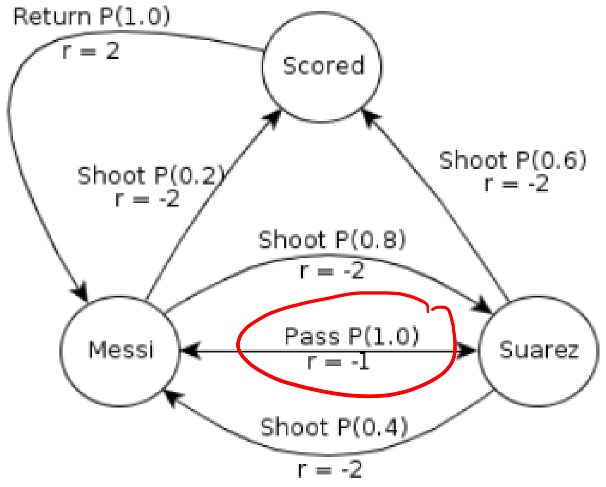
Problem 3: SARSA

Q-learning.

SARSA.

	Pass	Shoot	Return
Messi	-0.4	-0.8	-
Suarez	-0.7	-0.2	-
Scored	-	-	1.2

The following diagram shows the transition probabilities and rewards:



Consider again being in the state 'Suarez', Suarez passes the ball to Messi and then Messi decides to shoot. Show the SARSA update for the Pass action using a discount factor $\gamma = 0.9$ and learning rate $\alpha = 0.4$ and assuming a' (the next action to be execute) is ***Shoot***. Compare to the Q-learning update. What is different?

$$Q(s, a) = Q(s, a) + \alpha[r + \gamma\, \underline{Q(s', \pi(s'))} - Q(s, a)]$$

$$\underset{s}{\text{Suarez}} \xrightarrow[a]{\text{pass}} \underset{s'}{\text{Messi}} \xrightarrow[\pi(s')]{\text{shoot}}$$

$$Q(\text{Suarez}, \text{pass}) = Q(\text{Suarez}, \text{pass}) + \alpha[r + \gamma\, Q(\text{Messi}, \text{shoot}) - Q(\text{Suarez}, \text{pass})]$$

$$= -0.7 + 0.4[-1 + 0.9 \times (-0.8) - (-0.7)]$$

$$= -1.108.$$