## Planning, Learning and Decision Making

Group 27

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## Homework 5. Reinforcement learning

a)

```
In [1]: import numpy as np
    X = ("(4, \bar{b}, r)", "(5, \bar{b}, r)")
     S4bR = 0; S5bR = 1
    UP = 0; DOWN = 1; LEFT = 2; RIGHT = 3
    GAMMA = 0.99
     STEP SIZE = 0.1
    Q t = np.array([[3.23, 3.34, 3.25, 3.22], [3.08, 3.25, 3.57, 3.22]])
    # Slide 15 of lec21.pdf
     def Q_learning_update(x_t, a_t, c_t, x_t1):
         result = np.copy(Q_t)
         result[x_t, a_t] = Q_t[x_t, a_t] + STEP_SIZE * (c_t + GAMMA * np.min
     (Q_t[x_t1]) - Q_t[x_t, a_t])
         return result
    print("Q-values after a Q-learning update resulting from the transition
     at time step t:")
     Q_t1_Q_learning = Q_learning_update(S5bR, UP, 1.0, S5bR)
    for state, Q in zip(X, Q_t1_Q_learning):
print(state + ":", Q)
    Q-values after a Q-learning update resulting from the transition at time
    step t:
     (4, b̄, r): [3.23 3.34 3.25 3.22]
     (5, b̄, r): [3.17692 3.25
                                 3.57
                                          3.22 ]
```

b)

```
In [2]:
    # Slide 32 of lec21.pdf
    def SARSA_update(x_t, a_t, c_t, x_t1, a_t1):
        result = np.copy(Q_t)
        result[x_t, a_t] = Q_t[x_t, a_t] + STEP_SIZE * (c_t + GAMMA * Q_t[x_t])
    t1, a t1] - 0 t[x t, a t]
        return result
    print("Q-values after a SARSA update resulting from the transition at ti
    me step t:")
    Q t1 SARSA = SARSA update(S5bR, UP, 1.0, S5bR, RIGHT)
    for state, Q in zip(X, Q_t1_SARSA):
        print(state + ":", Q)
    Q-values after a SARSA update resulting from the transition at time step
    t:
    (4, b̄, r): [3.23 3.34 3.25 3.22]
    (5, b̄, r): [3.19078 3.25 3.57
                                         3.22
                                                ]
```

## c)

On-policy learning improves the same policy that is used to make exploration decisions, while off-policy learning improves a different policy than the one used to make exploration decisions. This results in on-policy conservatively learning a near-optimal policy instead of the optimal policy, unless policy improvement (e.g.  $\varepsilon$ -greedy with decaying  $\varepsilon$ ) is used, while off-policy learns the optimal policy at the expense of more mistakes (whose cost may be significant).

Q-learning (1.a) is off-policy as the Q-values are updated based on the optimal (in this case minimizing) action for the next state. On the other hand, SARSA (1.b) is on-policy as the Q-values are updated using the performed action for the next state, which was chosen by the same policy being improved.