

# ***Reinforcement Learning: with Python***

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S14490



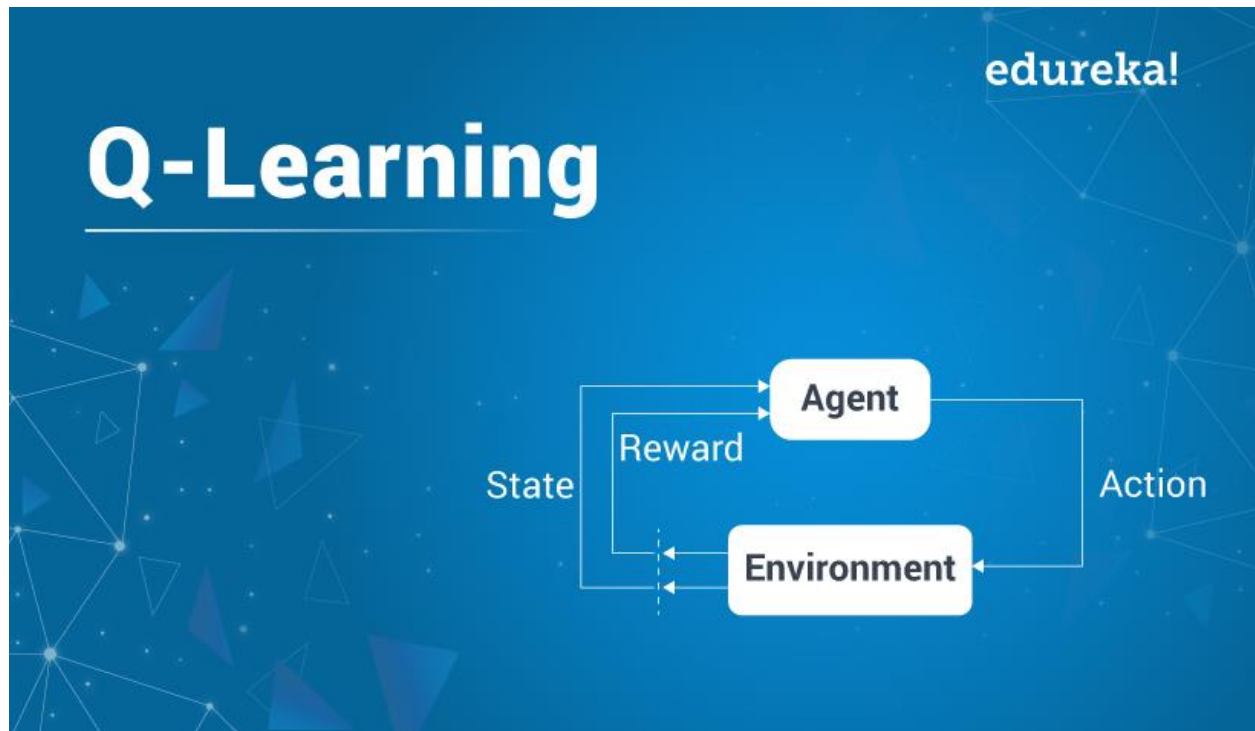
## What is reinforcement learning?

Reinforcement learning is the training of machine learning models to [make a sequence of decisions](#).

The agent learns to achieve a goal in an uncertain, potentially complex environment. In reinforcement learning, an artificial intelligence faces a game-like situation. The computer employs trial and error to come up with a solution to the problem. To get the machine to do what the programmer wants, the artificial intelligence gets either rewards or penalties for the actions it performs. Its goal is to maximize the total reward.

Although the designer sets the reward policy—that is, the rules of the game—he gives the model no hints or suggestions for how to solve the game. It's up to the model to figure out how to perform the task to maximize the reward, starting from totally random trials and finishing with sophisticated tactics and superhuman skills. By leveraging the power of search and many trials, reinforcement learning is currently the most effective way to hint machine's creativity. In contrast to human beings, artificial intelligence can gather experience from thousands of parallel gameplays if a reinforcement learning algorithm is run on a sufficiently powerful computer infrastructure.

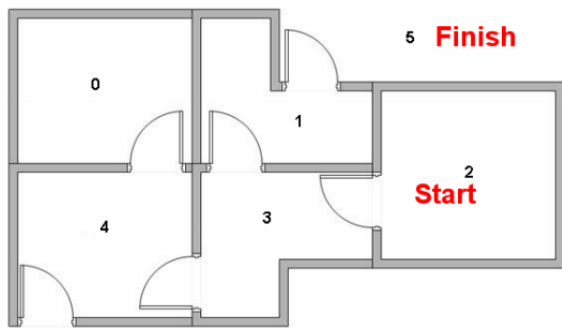
## What is Q-learning?



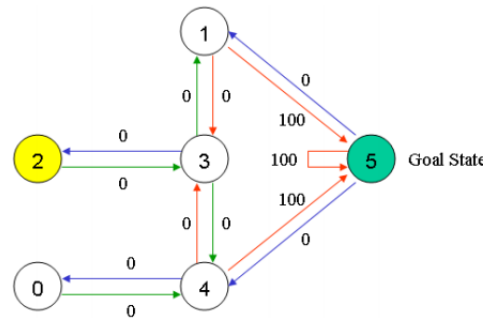
Q-learning is an off policy reinforcement learning algorithm that seeks to find the best action to take given the current state. It's considered off-policy because the q-learning function learns from actions that are outside the current policy, like taking random actions, and therefore a policy isn't needed. More specifically, q-learning seeks to learn a policy that maximizes the total reward.

## Part 2

An agent has to travel from one room (start state) to another (goal state) in the following house



Representing the goal using immediate rewards



What paths are available?  
What is the best path?

**Google colab Code:**

[https://colab.research.google.com/drive/1AeCQADifRCXqG1Mrvve\\_p727TNQ1XL6e?usp=sharing](https://colab.research.google.com/drive/1AeCQADifRCXqG1Mrvve_p727TNQ1XL6e?usp=sharing)

## Creating Graph (python)

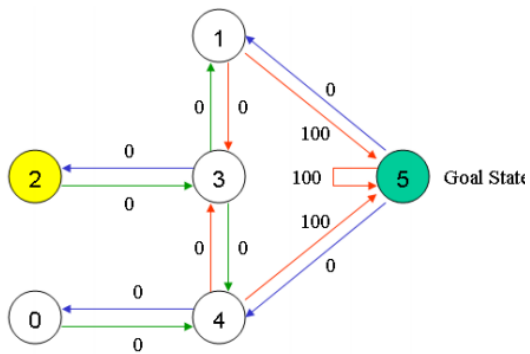
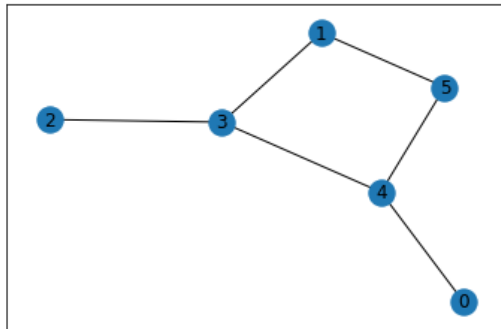


```
[ ] import numpy as np
import pylab as plt
```

```
# map cell to cell, add circular cell to goal point
points_list = [(0,4), (4,5), (4,3), (5,1), (1,3), (3,2)]
```

```
[ ] goal=5
```

```
[ ] import networkx as nx
G=nx.Graph()
G.add_edges_from(points_list)
pos = nx.spring_layout(G)
nx.draw_networkx_nodes(G,pos)
nx.draw_networkx_edges(G,pos)
nx.draw_networkx_labels(G,pos)
plt.show()
```



## Creating Matrix (python)



```
[ ] # how many points in graph? x points
MATRIX_SIZE = 6
```

```
[ ] # create matrix x*y
R = np.matrix(np.ones(shape=(MATRIX_SIZE, MATRIX_SIZE)))
R *= -1
```

```
[ ] # assign zeros to paths and 100 to goal-reaching point
for point in points_list:
    print(point)
    if point[1] == goal:
        R[point] = 100
    else:
        R[point] = 0

    if point[0] == goal:
        R[point[::-1]] = 100
    else:
        # reverse of point
        R[point[::-1]] = 0

# add goal point round trip
R[goal,goal] = 100
```

```
(0, 4)
(4, 5)
(4, 3)
(5, 1)
(1, 3)
(3, 2)
```

▶ R

```
matrix([[ -1.,  -1.,  -1.,  -1.,   0.,  -1.],
        [ -1.,  -1.,  -1.,   0.,  -1., 100.],
        [ -1.,  -1.,  -1.,   0.,  -1.,  -1.],
        [ -1.,   0.,   0.,  -1.,   0.,  -1.],
        [  0.,  -1.,  -1.,   0.,  -1., 100.],
        [ -1.,   0.,  -1.,  -1.,   0., 100.]])
```



## Octave (example not in above)

```
% -inf = no door between the rooms
R = [-inf, 0, -inf, 0, -inf, -inf, -inf;
     0, -inf, 0, 0, 0, -inf, -inf;
    -inf, 0, -inf, -inf, -inf, 0, 100;
     0, 0, -inf, -inf, -inf, -inf, 100;
    -inf, 0, -inf, -inf, -inf, 0, -inf;
    -inf, -inf, 0, -inf, 0, -inf, -inf;
    -inf, -inf, 0, 0, -inf, -inf, 100]
```

## Exploration (python)

```
Q = np.matrix(np.zeros([MATRIX_SIZE,MATRIX_SIZE]))

# learning parameter
gamma = 0.8

initial_state = 2

def available_actions(state):
    current_state_row = R[state,]
    av_act = np.where(current_state_row >= 0)[1]
    return av_act

available_act = available_actions(initial_state)

def sample_next_action(available_actions_range):
    next_action = int(np.random.choice(available_act,1))
    return next_action

action = sample_next_action(available_act)

def update(current_state, action, gamma):

    max_index = np.where(Q[action,] == np.max(Q[action,]))[1]

    if max_index.shape[0] > 1:
        max_index = int(np.random.choice(max_index, size = 1))
    else:
        max_index = int(max_index)
    max_value = Q[action, max_index]

    Q[current_state, action] = R[current_state, action] + gamma * max_value
    print('max_value', R[current_state, action] + gamma * max_value)

    if (np.max(Q) > 0):
        return(np.sum(Q/np.max(Q)*100))
    else:
        return (0)

update(initial_state, action, gamma)
```

max\_value 0.0  
0

## Exploiting (python)

```
# Training
scores = []
for i in range(700):
    current_state = np.random.randint(0, int(Q.shape[0]))
    available_act = available_actions(current_state)
    action = sample_next_action(available_act)
    score = update(current_state, action, gamma)
    scores.append(score)
    print('Score:', str(score))

print("Trained Q matrix:")
print(Q/np.max(Q)*100)
```

```
Trained Q matrix:
[[ 0.         0.         0.         0.         79.9999946
  0.         ]
 [ 0.         0.         0.         63.99999568  0.
 100.        ]
 [ 0.         0.         0.         63.99999568  0.
 0.         ]
 [ 0.         80.         51.19999222  0.         79.99998785
 0.         ]
 [ 63.99999568  0.         0.         64.         0.
 100.        ]
 [ 0.         79.99993921  0.         0.         80.
 100.        ]]
```

## Octave

$$Q = \begin{matrix} & \begin{matrix} 0 & 1 & 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} & \begin{bmatrix} 0 & 0 & 0 & 0 & 80 & 0 \\ 0 & 0 & 0 & 64 & 0 & 100 \\ 0 & 0 & 0 & 64 & 0 & 0 \\ 0 & 80 & 51 & 0 & 80 & 0 \\ 64 & 0 & 0 & 64 & 0 & 100 \\ 0 & 80 & 0 & 0 & 80 & 100 \end{bmatrix} \end{matrix}$$

Divided by the max



## Testing

```
▶ # Testing
current_state = 2
steps = [current_state]

while current_state != 5:

    next_step_index = np.where(Q[current_state,]
                               == np.max(Q[current_state,]))[1]

    if next_step_index.shape[0] > 1:
        next_step_index = int(np.random.choice(next_step_index, size = 1))

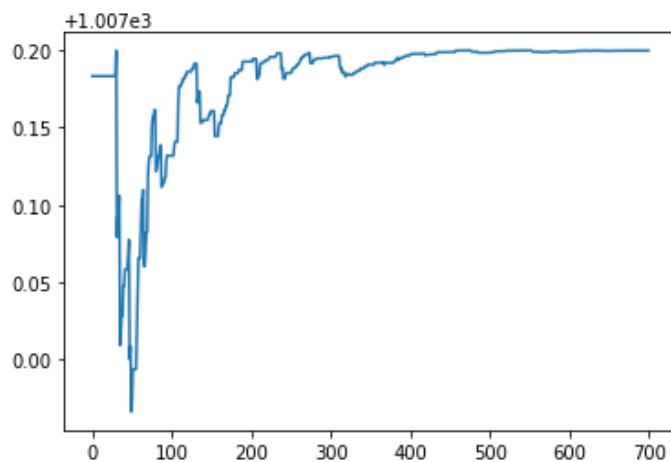
    else:
        next_step_index = int(next_step_index)

    steps.append(next_step_index)
    current_state = next_step_index

print("Most efficient path:")
print(steps)

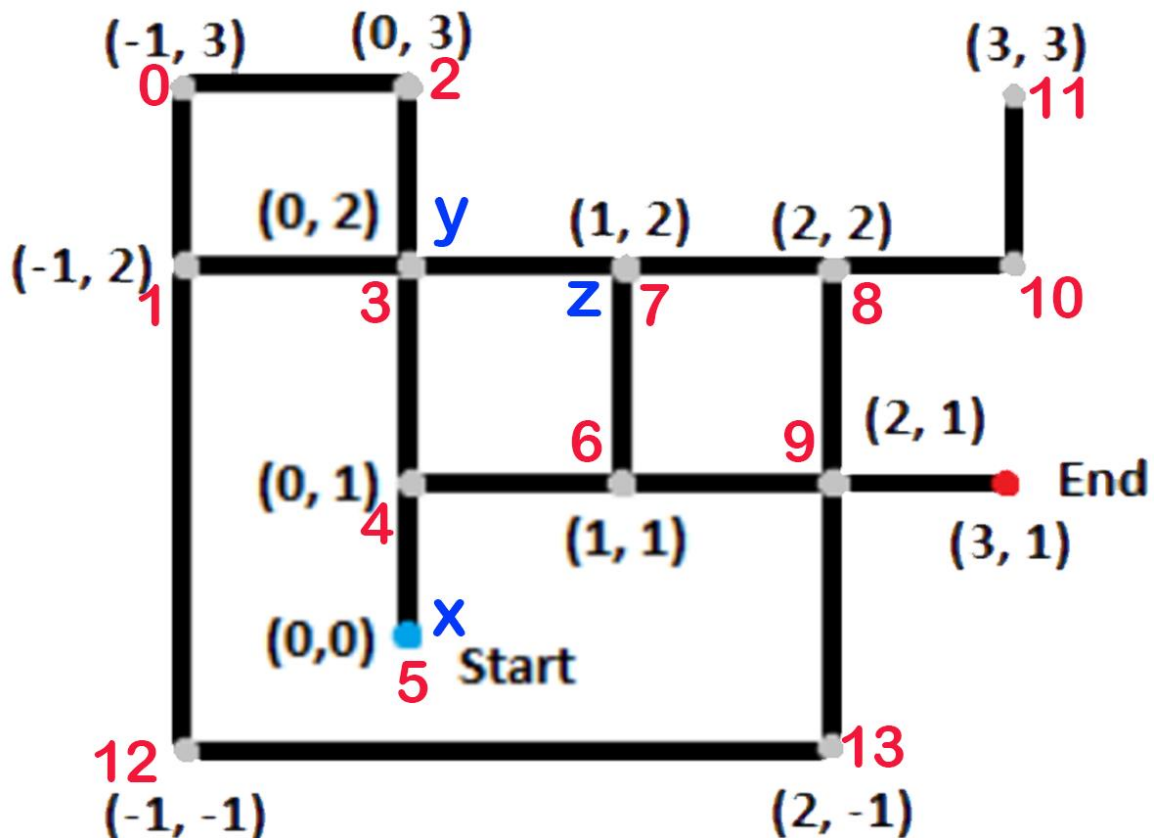
plt.plot(scores)
plt.show()
```

☞ Most efficient path:  
[2, 3, 1, 5]



**When we compare result/output of Octave vs Python,  
we get same output with both but it will be little bit different  
when considering the Q-table.**

## Part 3

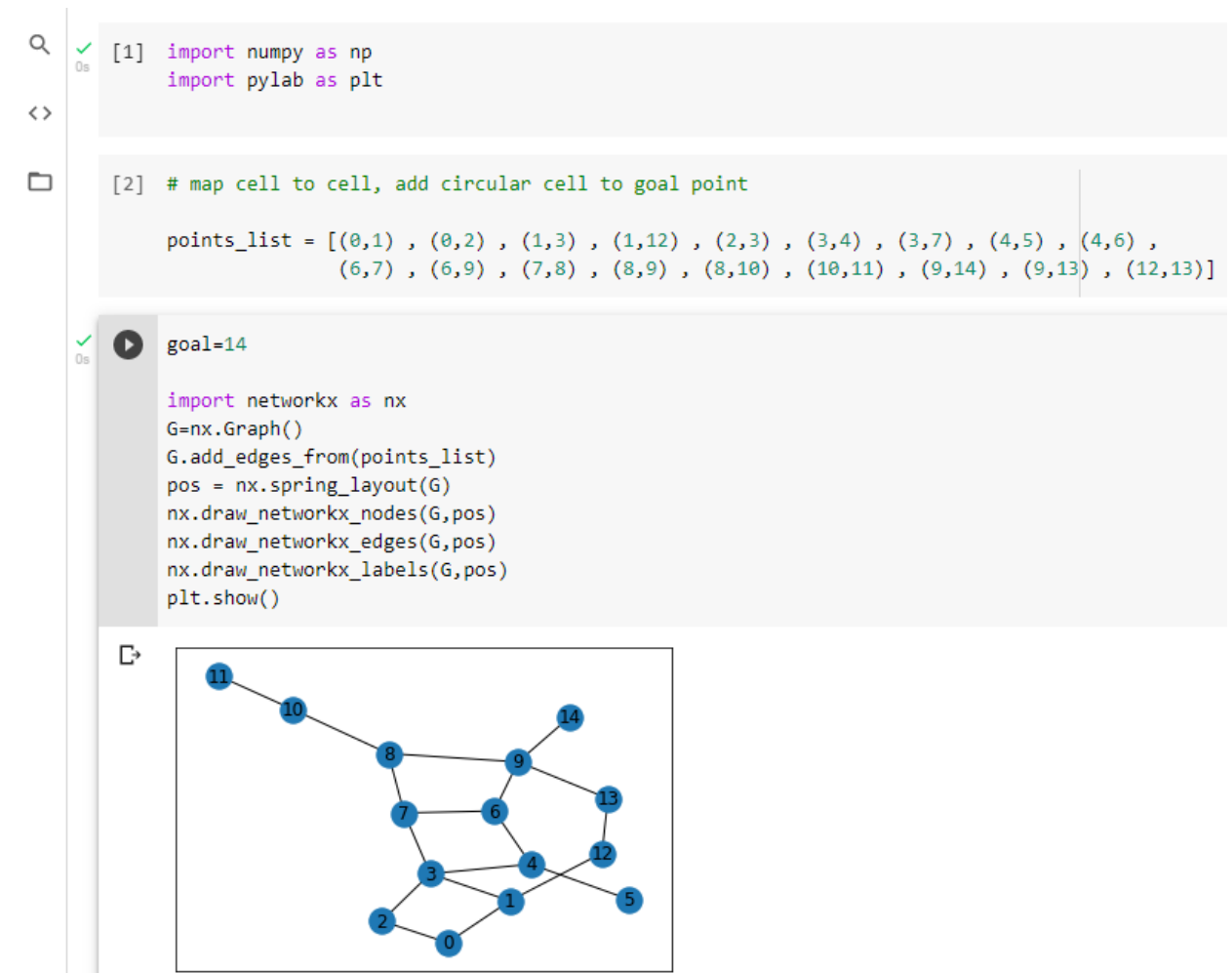


- You are required to build a maze solving robot who should be able to reach the end point when its placed at any starting point. The layout of the maze (paths) is given below

## Google colab code:-

[https://colab.research.google.com/drive/1uwMZz0jxH1pwxA6ZzwAl\\_ef3v0Sx9-oZ?usp=sharing](https://colab.research.google.com/drive/1uwMZz0jxH1pwxA6ZzwAl_ef3v0Sx9-oZ?usp=sharing)

## Graph



# Making Matrix

```
# how many points in graph? x points
MATRIX_SIZE = 15

# create matrix x*y
R = np.matrix(np.ones(shape=(MATRIX_SIZE, MATRIX_SIZE)))
R *= -1

# assign zeros to paths and 100 to goal-reaching point
for point in points_list:
    print(point)
    if point[1] == goal:
        R[point] = 100
    else:
        R[point] = 0

    if point[0] == goal:
        R[point[::-1]] = 100
    else:
        # reverse of point
        R[point[::-1]] = 0

# add goal point round trip
R[goal,goal]= 100

R
```

(0, 1)  
(0, 2)  
(1, 3)  
(1, 12)  
(2, 3)  
(3, 4)  
(3, 7)  
(4, 5)  
(4, 6)  
(6, 7)  
(6, 9)  
(7, 8)  
(8, 9)  
(8, 10)  
(10, 11)  
(9, 14)  
(9, 13)  
(12, 13)

```
matrix([[ -1.,   0.,   0.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [   0.,  -1.,  -1.,   0.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,
         -1.,  -1.,   0.,  -1.,  -1.],
        [   0.,  -1.,  -1.,   0.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,   0.,   0.,  -1.,   0.,  -1.,  -1.,   0.,  -1.,  -1.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,   0.,  -1.,   0.,   0.,  -1.,  -1.,  -1.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,  -1.,   0.,  -1.,  -1.,  -1.,  -1.,  -1.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,  -1.,   0.,  -1.,  -1.,   0.,  -1.,   0.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,   0.,  -1.,  -1.,   0.,  -1.,   0.,  -1.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,   0.,  -1.,   0.,
         0.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,  -1.,  -1.,  -1.,   0.,  -1.,   0.,  -1.,
         -1.,  -1.,  -1.,   0., 100.],
        [ -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,   0.,  -1.,
         -1.,   0.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,
         0.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,   0.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,
         -1.,  -1.,  -1.,   0.,  -1.],
        [ -1.,  -1.,   0.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,   0.,
         -1.,  -1.,  -1.,  -1.,  -1.],
        [ -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,  -1.,   0.,
         -1.,  -1.,  -1.,  -1., 100.]])
```

## Exploration

```
✓ 0s [8] Q = np.matrix(np.zeros([MATRIX_SIZE,MATRIX_SIZE]))

# learning parameter
gamma = 0.8

initial_state = 5

def available_actions(state):
    current_state_row = R[state,]
    av_act = np.where(current_state_row >= 0)[1]
    return av_act

available_act = available_actions(initial_state)

def sample_next_action(available_actions_range):
    next_action = int(np.random.choice(available_act,1))
    return next_action

action = sample_next_action(available_act)

def update(current_state, action, gamma):

    max_index = np.where(Q[action,] == np.max(Q[action,]))[1]

    if max_index.shape[0] > 1:
        max_index = int(np.random.choice(max_index, size = 1))
    else:
        max_index = int(max_index)
    max_value = Q[action, max_index]

    Q[current_state, action] = R[current_state, action] + gamma * max_value
    print('max_value', R[current_state, action] + gamma * max_value)

    if (np.max(Q) > 0):
        return(np.sum(Q/np.max(Q)*100))
    else:
        return (0)

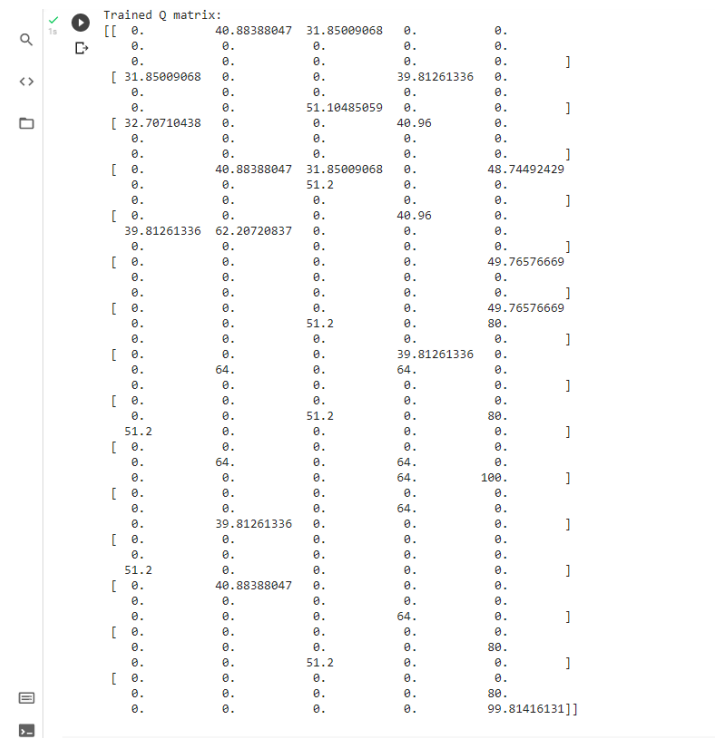
update(initial_state, action, gamma)

max_value 0.0
0
```

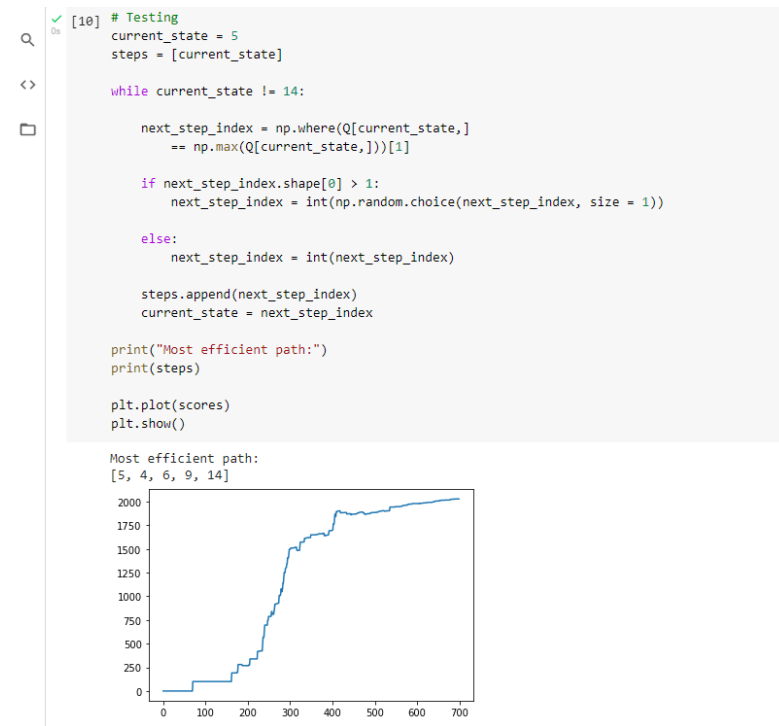
## Exploiting

```
✓ 1s # Training
scores = []
for i in range(700):
    current_state = np.random.randint(0, int(Q.shape[0]))
    available_act = available_actions(current_state)
    action = sample_next_action(available_act)
    score = update(current_state,action,gamma)
    scores.append(score)
    print ('Score:', str(score))

print("Trained Q matrix:")
print(Q/np.max(Q)*100)
```



## Testing



- Give the resulting q-tables with calculations after the following state transitions during the exploration.

❖ Start = (0, 0); Actions: UP, RIGHT, RIGHT, RIGHT

❖ Start = (0, 2), Actions: DOWN, RIGHT, UP, RIGHT, DOWN, RIGHT

❖ Start = (1, 2); Actions: DOWN, RIGHT, RIGHT

**1. Start = (0, 0); Actions: UP, RIGHT, RIGHT, RIGHT**

```
Q = np.matrix(np.zeros([15,15]))
gamma=0.8

## Start=(0,0)
x = [5,4,6,9,14]
i=0
while i != (len(x)-1):
    action = x[i+1]
    update(x[i],action,gamma)
    i=i+1

print("\nQ matrix after x")
print(Q)
```

[illegible]



## 2. Start = (0, 2), Actions: DOWN, RIGHT, UP, RIGHT, DOWN, RIGHT

```
✓ [15] ## Start=(0,2)
0s y = [3,4,6,7,8,9,14]
    i=0
    while i != (len(y)-1):
        print("abc")
        action = y[i+1]
        update(y[i],action,gamma)
        i=i+1

    print("\nQ matrix after y")
    print(Q)
```

```
abc
max_value 0.0
abc
max_value 0.0
abc
max_value 0.0
abc
max_value 0.0
abc
max_value 80.0
abc
max_value 100.0
```

```
Q matrix after y
[[ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  80.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
 100.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]]
```

### 3. Start = (1, 2); Actions: DOWN, RIGHT, RIGHT

```
✓ [16] ## Start=(1,2)
0s   z = [7,6,9,14]
      i=0
      while i != (len(z)-1):
          print("abc")
          action = z[i+1]
          update(z[i],action,gamma)
          i=i+1

      print("\nQ matrix after z")
      print(Q)
```

```
abc
max_value 0.0
abc
max_value 80.0
abc
max_value 100.0
```

```
Q matrix after z
[[ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  80.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  80.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
 100.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.]]
```

- Now, what would be the sequence of states if the robot exploits to reach the goal starting from (0, 0)?  
Explain your answer

When robot exploits it's Q matrix to reach the goal starting from (0,0) , robot will choose the path Action: UP , RIGHT , RIGHT , RIGHT [ 5 , 4 , 6 , 9 , 14 ] or [ (0,0) ,(0,1) , (1,1) ,(2,1) , (3,1) ] because it is the most efficient path for it..

### Reference:

- <https://deepsense.ai/what-is-reinforcement-learning-the-complete-guide/>
- <https://towardsdatascience.com/simple-reinforcement-learning-q-learning-fcddc4b6fe56>
- <https://www.edureka.co/blog/q-learning/>
- GNU Octave Tutorial