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```
In [ ]: import numpy as np
import random
```

• Here we set our algorithm parameter

$$Q^{new}(s_t, a_t) \leftarrow (1 - \alpha) \cdot \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \underbrace{\left(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_{a} Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}\right)}$$

learned value

```
In [2]: num_episodes = 10000
    max_steps_per_episodes = 20
    learning_rate = 0.1
    discount_rate = 0.99

    exploration_rate = 1
    max_exploration_rate = 1
    min_exploration_rate = 0.01
    exploration_decay_rate = 0.01
```

• Just set up few things to consider

0	1	2
3	4	5
6	7	8

Moon_Sun_Star is showing the starting position and Moon_Sun_End the end position of moons and stars based on indexes above moves array define proper moves from one index to another, If it is 1, you can go to another house

Q table will be represented like this:

	right •	down ひ	left ひ	up •
	0	1	2	3
0	0			
1	0			
2				
3	0			
4	0			
5				
6	0		0	0
7				
8	0	0	0	0

nouses index

```
In [3]: | # Define the actions
        actions = [0,1,2,3,4,5,6,7,8]
        # Define the Moon and Sun position at start
        Moon_Sun_Start = {
             <u>'0'</u>: '*',
            '1' : '*',
            '2' : '*',
            '3' : '/',
             '4' : '*'
             '5' : '/',
             '6' : '/',
'7' : ' ',
             '8' : '/'
        }
        # Define the Moon and Sun position at the end
        Moon_Sun_End = {
            '0':'',
             '1' : '/',
             '2' : '*',
             '3' : '/',
             '4' : '*',
            '5' : '/',
             '6' : '*',
            '7' : '/',
             '8' : '*'
        # Define proper moves
        moves = np.array([[0,1,0,1,0,0,0,0,0]],
                       [1,0,1,0,1,0,0,0,0],
                       [0,1,0,0,0,1,0,0,0],
                       [1,0,0,0,1,0,1,0,0],
                       [0,1,0,1,0,1,0,1,0],
                       [0,0,1,0,1,0,0,0,1],
                       [0,0,0,1,0,0,0,1,0],
                       [0,0,0,0,1,0,1,0,1],
                       [0,0,0,0,0,1,0,1,0]]
         rewards_all_episodes = []
        q_table = np.array(np.zeros([9,4]))
```

• We set our reward function this way that

The function checks that we have reached the goal and returns the score and result

we refresh MN also (MN shows location of moons and suns for each episode)

```
In [4]: # Reward function
def situation(state, new_state, MN):
    global Moon_Sun_End
    MN[str(state)], MN[str(new_state)] = MN[str(new_state)], MN[str(state)]
    point = 0
    for i in range(9):
        if MN[str(i)] == Moon_Sun_End[str(i)]:
            point += 1
    if point == 9:
        return point, True
    return 0, False
```

• Q-Learning In this section based on whether we want to explore or exploite

We set new state and then after getting the reward, update Q table using this equation

$$Q^{new}(s_t, a_t) \leftarrow (1 - \alpha) \cdot \underbrace{Q(s_t, a_t)}_{\text{old value}} + \underbrace{\alpha}_{\text{learning rate}} \cdot \underbrace{\left(\underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_{a} Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}\right)}$$

If we reached our goal the route will be printed. At the end of each episode we update exploration rate using exponential decay.

```
In [ ]: | for episode in range(num_episodes):
            MN = Moon_Sun_Start.copy()
            route = [7]
            state = 7
            done = False
            reward_current_episode = 0
            for step in range(max_steps_per_episodes):
                # Exploration-Exploitation trade-off
                exploration_rate_threshold = random.uniform(0, 1)
                if exploration_rate_threshold > exploration_rate and np.argmax(q_table[state,:]) != 0:
                    action = np.argmax(q_table[state,])
                    if action == 0:
                        new_state = state + 1
                    elif action == 1:
                        new state = state + 3
                    elif action == 2:
                        new_state = state - 1
                    else:
                        new_state = state - 3
                else:
                    playable_actions = []
                    for j in range(9):
                         if moves[state, j] > 0:
                            playable_actions.append(j)
                    new_state = np.random.choice(playable_actions)
                    while(len(route) >= 2 and new_state == route[-2]):
                         new_state = np.random.choice(playable_actions)
                # Computing reward and Situation
                reward, done = situation(state, new_state, MN)
                # Updating Q table based on action and reward
                if new_state > state:
                    if state + 1 == new_state:
                        action = 0 #right
                    else:
                        action = 1 #down
                else:
                    if state - 1 == new_state:
                        action = 2 \# left
                    else:
                         action = 3 #up
                q_table[state, action] = q_table[state, action] * \
                    (1 - learning_rate) + learning_rate * (reward + discount_rate * np.max(q_table[new_state, :]))
                # Upadting route and checking if we reached the goal or not
                route.append(new_state)
                state = new_state
                reward_current_episode += reward
                if done == True:
                    print("\n YEEEEEEEES! ")
                    print(route)
                    break
            # Updating exploration rate
            exploration_rate = min_exploration_rate + (max_exploration_rate - min_exploration_rate) * \
                np.exp(-exploration_decay_rate * episode)
            rewards_all_episodes.append(reward_current_episode)
        YEEEEEEES!
```

[7, 4, 1, 2, 5, 4, 1, 0, 3, 6, 7, 8, 5, 2, 1, 0] YEEEEEEEES! [7, 8, 7, 4, 5, 2, 1, 0, 3, 6, 7, 8, 5, 4, 1, 0] YEEEEEEEES! [7, 4, 5, 2, 1, 0, 3, 6, 7, 8, 5, 4, 1, 0]YEEEEEEEES! [7, 4, 1, 0, 3, 6, 7, 4, 5, 2, 5, 8, 7, 4, 1, 0] YEEEEEEES! [7, 4, 5, 2, 1, 0, 3, 6, 7, 8, 5, 4, 1, 0]

YEEEEEEES!

[7, 4, 1, 0, 3, 4, 5, 2, 1, 4, 5, 8, 7, 6, 3, 0]

Final Outputs

Finaly we check our q-table

In [6]: print(" \n", q_table)

```
[[0.01673581 0.01665507 0. 0. ]
[0.01677902 0.01673429 0.01668266 0. ]
[0. 0.01678469 0.01681967 0. ]
[0.01670197 0.01670986 0. 0.01669494]
[0.01673067 0.01664929 0.01666069 0.01669771]
[0. 0.00893354 0.01662282 0.01346833]
[0.01671964 0. 0. 0.0166746 ]
[0.01668542 0. 0.01667634 0.01667448]
[0. 0. 0.00178249 0.01664781]]
```

Q table is showing this

		right ₽	down &	left ひ	up •
		0	1	2	3
houses index	0	0.0709285	0.074569	0	0
	1	0.0652862	0.0642932	0.0725043	0
	2	0	0.0637064	0.0755429	0
	3	0.074624	0.0745188	0	0.0745784
	4	0.0637843	0.0747352	0.0710959	0.0655562
	5	0	0.0668559	0.0635876	0.0635746
	6	0.0709761	0	0	0.0742106
	7	0.0751379	0	0.0740347	0.0750802
	8	0	0	0.0751039	0.063455

houses index