SolvingMazes: Dyna-Q+ Agent

Achi's Projects (https://github.com/QuantumNano-Al/PROJECTS)

The DynaQ+ algorithm is more robust than DynaQ. It provides a solution to environment dynamics changing and thus making its model inaccurate

For the DynaQ+ Agent we will be adding two new parameters state visitation count τ and scaling parameter κ .

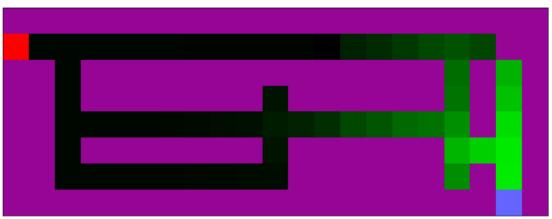
Where r is the modeled reward for a transition which hasn't been visited in $\tau(s,a)$ time steps, the planning updates are done using $r+\kappa\sqrt{\tau(s,a)}$ as the reward instead

```
In [1]: import numpy as np
        import sklearn.preprocessing as sc
        import matplotlib.pyplot as plt
        import cv2
        import pandas as pd
        import operator
        class Maze:
            def __init__(self, maze, rewards = {'goal':1000000,'wall':-15, 'other':-1}):
                 """# Read file and set height and width of maze
                 with open(filename) as f:
    maze = f.read()"""
                 self.rewards=rewards
                 # Validate start and goal
                 if maze.count("A") != 1:
                     raise Exception("maze must have exactly one start point")
                 if maze.count("B") != 1:
                     raise Exception("maze must have exactly one goal")
                 self.actions = ["up", "down", "left", "right"]
                 # Determine height and width of maze
                 maze = maze.splitlines()
                 self.height = len(maze)
                 self.width = max(len(line) for line in maze)
                 self.states = []
                 # Keep track of walls
                 self.walls = []
                 self.wall cords = []
                 for i in range(self.height):
                     row = []
                     for j in range(self.width):
                          try:
                              if maze[i][j] == "A":
                                  self.start = (i, j)
                                  row.append(False)
                                  self.states.append((i,j))
                              elif maze[i][j] == "B":
                                  self.goal = (i, j)
                                  row.append(False)
                                  self.states.append((i,j))
                              elif maze[i][j] ==
                                  row.append(False)
                                  self.states.append((i,j))
                              else:
                                  row.append(True)
                                  self.wall_cords.append((i,j))
                          except IndexError:
                              row.append(False)
                              self.states.append((i,j))
                     self.walls.append(row)
                 self.state_count = len(self.states)
                 self.solution = None
                 self.V = dict(zip(self.states, self.state_count*[0]))
                 self.pi = dict(zip(self.states, self.state_count*[0]))
                 for s in self.states:
                     avail actions = self.actions
                     self.pi[s] = avail actions[0]
                 self.pi1 = dict(zip(self.states, self.state_count*[0]))
                 solution = self.solution[1] if self.solution is not None else None
                 for i, row in enumerate(self.walls):
                     for j, col in enumerate(row):
                         if col:
                              print("#", end="")
                          elif (i, j) == self.start:
    print("A", end="")
                          elif (i, j) == self.goal:
    print("B", end="")
                          elif solution is not None and (i, j) in solution:
    print("*", end="")
                          else:
                             print(" ", end="")
                     print()
                 print()
            def neighbors(self, state, a = None):
                    This function takes in a state and returns all available actions for that state the next state
                    and reward if each action is take, with a specific transition probability"""
                 row, col = state
                 candidates = [
                     ("up", (row - 1, col)),
                     ("down", (row + 1, col)),
("left", (row, col - 1)),
("right", (row, col + 1))
                 terminal = False
                 result = []
                 for action, (r, c) in candidates:
                     if (r,c) == self.goal: terminal = True
                     if 0 <= r < self.height and 0 <= c < self.width and not self.walls[r][c]:
                          if (row, col) == self.goal:
                              (r, c) = self.goal; terminal = True
```

```
reward = self.rewards['goal'] if ((r,c) == self.goal) or (state == self.goal) else self.rewards['other']
            trans prob = 1
            result.append((action, (r, c), reward, trans_prob, terminal))
    actions = [tup[0] for tup in result]
    if a:
        R = []
        if a in actions:
            inx = actions.index(a)
            R.append((result[inx]))
            R.append((a, (row,col), self.rewards['wall'], 1, terminal))
    return result
def plot_state_values(self):
    val = np.array(list(self.V.values())).reshape(-1,1)
    va = sc.MinMaxScaler(feature_range=(0, 255)).fit_transform(val).flatten()
    V = \{\}
    for i in range(len(va)):
        V[list(self.V.keys())[i]] = va[i]
    # create a black image
    img = np.ones((self.height,self.width,3), np.uint8)
    for item in V.items():
        (r,c),vx = item
img[r,c] = [0,vx,0]
    for r,c in self.wall_cords:
        img[r,c] = [150,5,150]
    img[self.start[0],self.start[1]] = [255,0,0]
    img[self.goal[0],self.goal[1]] = [100,100,255]
    def showimg(img):
        plt.figure(figsize = (15,15))
        plt.imshow(img, cmap='viridis')
        plt.xticks([])
        plt.yticks([])
        #plt.colorbar()
        plt.show()
    showimg(img)
    def policy_(s):
        row, col = s
        candidates = [
            ("up", (row - 1, col)),
("down", (row + 1, col)),
("left", (row, col - 1)),
("right", (row, col + 1))
        1
        if s in self.wall cords:
            return ('WALL!!!')
            values = \{a: self. V[r,c] \text{ for a,(r,c) in candidates if } 0 <= r < self.height and } 0 <= c < self.width and not self.walls[r][c]\}
            values = {v:k for k,v in values.items()}
            best = values[max(values)]
        return best
    pi = np.zeros((self.height, self.width)).astype('str')
   pi = np.where(pi=='0.0', 'wall', pi)
    for item in self.pi.kevs():
        action = policy_(item)
        r.c = item
        pi[r,c] = action
        img[r,c] = candidates[action]
    img[self.start[0],self.start[1]] = [255,0,0]
    img[self.goal[0],self.goal[1]] = [100,100,255]
    def showimg(img):
        plt.figure(figsize = (15,15))
plt.imshow(img, cmap='viridis', )
        plt.yticks(list(range(self.height)))
        plt.xticks(list(range(self.width)))
        plt.title("POLICY\n\nRED => up\nBLUE => down\nGREEN => left\nYELLOW => right")
        #plt.colorbar()
        plt.show()
    showimg(img)
    return img
```

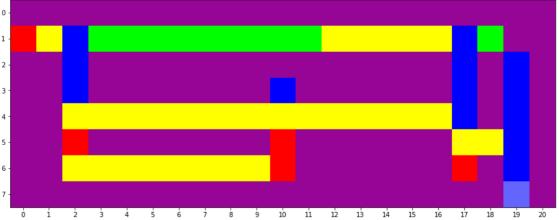
```
In [2]: class DynaQ(Maze):
                   def __init__(self, maze, rewards = {'goal':1000000,
                                                                                    'wall' -- 15
                                                                                    'other':-1},
                                                           info = {} ):
                         Maze.__init__(self, maze, rewards)
                          self.epsilon = info.get('epsilon', 0.9) # Exporation parameter
                          self.r = np.random.RandomState(seed=12345)
                         self.episodes =info.get('episodes', 200)
self.max_steps =info.get('max_steps', 1500)
                         self.alpha = info.get('alpha',0.1) # step size
self.gamma = info.get('gamma',.99) # discount factor
self.kappa = info.get('kappa',.001) # Scalling parameter
                          self.planning steps = info.get('planning steps',50)
                          self.tau = pd.DataFrame(np.zeros((self.state_count, len(self.actions))),columns=self.actions, index=self.states).to_dict(orient='index
                   def func_q(self, states,n_states,n_actions,kind = 'random'):
                                return dict(zip(states,np.ones((n_states,n_actions)).tolist()))
                          elif kind == 'zeros'
                                return dict(zip(states,np.zeros((n_states,n_actions)).tolist()))
                          elif kind =='random'
                                return dict(zip(states,np.round(self.r.randn(n_states,n_actions),2).tolist()))
                          else : raise NameError("Wrong input: please use ['ones', 'zeros', 'random']")
                   def argmax(self, test_array):
                          return self.r.choice(np.flatnonzero(np.array(test_array)==np.array(test_array).max()))
                   def epsilon_greedy(self, Q, epsilon, actions, state, train=False):
                          current_q = Q[state]
                          if self.r.rand() < epsilon:</pre>
                                action = self.r.choice(actions)
                                return action
                         else:
                                action = self.argmax(current a)
                          return actions[action]
                   def sigmoid(self,a):
                          import numpy as np
                          s = np.divide(1,1+np.exp(-a))
                          return s
                          self.Q = self.func_q(self.states,self.state_count,len(self.actions),kind = 'zeros')
                          self.model = {} # model is a dictionary of dictionaries, which maps states to actions to (reward, next_state) tuples
                          def update_model(s,a,s_,reward):
                                if s in self.model: self.model[s][a] = (s_,reward) # If the agent has been in this state before, update the action/reward
                                else:
                                      self.model[s] = {a:(s_,reward)} # else add new state and action to model
                                       # actions that had never been tried are now going to be considered. The initial model for such actions would be
                                       # to lead back to the previous state and have a reward of zero
                                      for action in self.actions:
                                             if action != a:
                                                   self.model[s][a] = (s, 0)
                         def planning():
                                for i in range(self.planning steps):
                                      s = list(self.model.keys())[self.r.randint(len(self.model.keys()))]
                                      a = self.r.choice(list(self.model[s].keys()))
                                      (s_,reward) = self.model[s][a]
                                      reward += self.kappa*np.sqrt(self.tau[s][a])
                                      q_ = self.Q[s_]
                                           = self.actions[self.argmax(q_)] # Action in the next state does not follow policy. It is rather selected to maximise utility
                                       if terminal:
                                            self.Q[s][self.actions.index(a)] += self.alpha * (reward - self.Q[s][self.actions.index(a)])
                                             self.Q[s][self.actions.index(a)] += self.alpha * (reward + self.gamma*max(q_) \setminus self.Q[s][self.actions.index(a)] += self.gamma*max(q_) \  (self.gamma*max(q_) \  (self.gamma*
                                                                                                                              - self.Q[s][self.actions.index(a)])
                          self.time_steps = pd.DataFrame()
                          for episode in range(self.episodes):
                                total_reward = 0 # This sets the total reward obtained during this episode
                                s = self.states[self.r.randint(len(self.states))]
                                a = {\tt self.epsilon\_greedy}({\tt Q=self.Q}, \ {\tt epsilon=self.epsilon}, \ {\tt actions=self.actions}, \ {\tt state=s})
                                t = 0
                                terminal = False
                                while t < self.max steps:</pre>
                                      t+=1
                                      self.tau = {k:{kk:vv+1 for kk,vv in v.items()} for k,v in self.tau.items()}
                                      self.tau[s][a] = 0
                                        _,s_, reward, p,terminal = self.neighbors(s,a)[0]
                                      total_reward += reward
                                      q_ = self.Q[s_] # Action values in the next state
                                      a_ = self.epsilon_greedy(Q=self.Q, epsilon=self.epsilon, actions=self.actions, state=s)
                                      reward += self.kappa*np.sqrt(self.tau[s][a])
                                      if terminal:
                                             self.Q[s][self.actions.index(a)] += self.alpha * (reward - self.Q[s][self.actions.index(a)])
                                             self.Q[s][self.actions.index(a)] += self.alpha * (reward + self.gamma*self.Q[s_][self.actions.index(a_)] \setminus
                                                                                                                              - self.Q[s][self.actions.index(a)])
                                      update_model(s,a,s_,reward)
                                       # Carry out planning only when there is a complete episode with rewards returned
                                      if len(self.time_steps)>0:
                                             ts = self.time_steps[self.time_steps.rewards!=0]
                                             if len(ts)>0:planning()
```

```
s, a = s_, a_
if terminal:
                          self.time_steps = self.time_steps.append(
                             pd.Series({'episode':int(episode), 'steps':t, 'rewards':total_reward}), ignore_index=True)
                          break
                   if t%10==0:
                      print(f'.',end='')
               self.pi = {}
               self.V = \{\}
               for k,v in self.Q.items():
                   self.pi[(k)] = self.actions[self.argmax(v)]
self.V[(k)] = max(v)
               max_r = max([v for k,v in self.V.items()])
               self.V[self.goal] = max_r
               img = self.plot_state_values()
               #return V,pi
        4
## ###### ##### # #
        ##
                        # #
        ## ###### #####
        ############B#"""
In [4]: | print(maze0)
        ## ###### ##### # #
        ##
                         # #
        ## ###### #####
                          #
                  ###### # #
        ##
        In [5]: info = {'episodes': 50, 'max_steps': 5000, 'alpha': 0.1, 'epsilon':.1, 'planning_steps':20, 'kappa':.5}
rewards = {'goal':10000, 'wall':-1, 'other':0}
        m = DynaQ(maze = maze0, rewards = rewards, info = info)
        m.run()
        #t = m.time_steps; t[t.rewards!=0][['episode','steps']]
```



POLICY

RED => up BLUE => down GREEN => left YELLOW => right



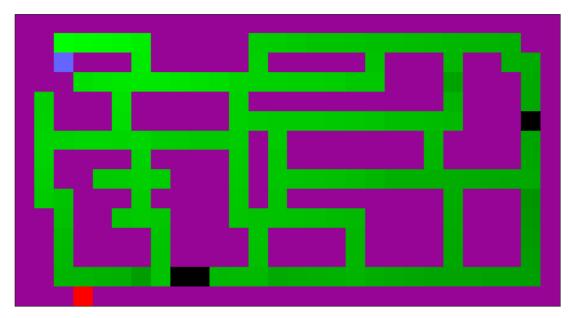
```
In []:
```

In []:

In []:

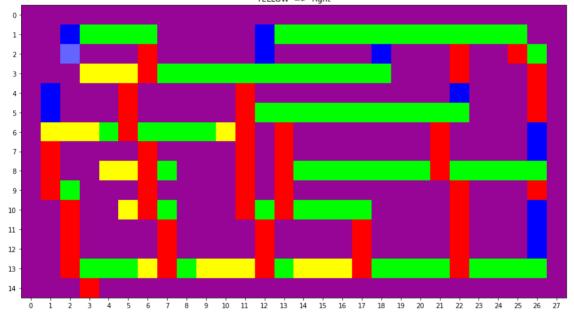
```
In [8]: info = {'episodes': 200,'max_steps': 5000,'alpha': 0.1,'epsilon':.1, 'planning_steps':100, 'kappa':.5}
    rewards = {'goal':10000000,'wall':-50, 'other':0}
    m = DynaQ(maze = maze, rewards = rewards, info = info)
    m.run()
    #t = m.time_steps; t[t.rewards!=0][['episode','steps']]
```

......



POLICY

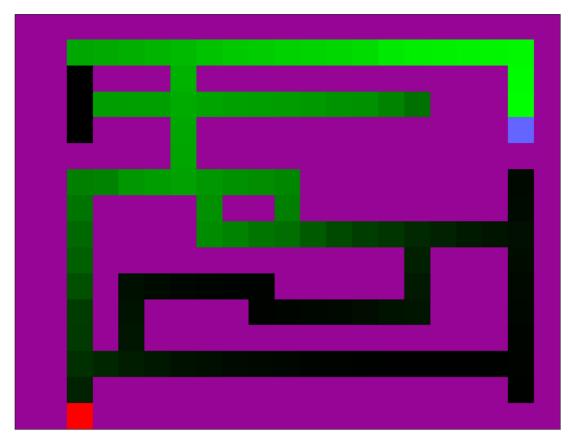
RED => up BLUE => down GREEN => left YELLOW => right



In [10]: print(maze1)

```
In [11]: info = {'episodes': 50, 'max_steps': 5000, 'alpha': 0.1, 'epsilon':.1, 'planning_steps':20}
    rewards = {'goal':100000000, 'wall':-100, 'other':0}
    m = DynaQ(maze = maze1, rewards = rewards, info = info)
    m.run()
    #t = m.time_steps; t[t.rewards!=0][['episode', 'steps']]
```

. . . .



POLICY

RED => up BLUE => down GREEN => left YELLOW => right

