```
import os
In [ ]:
In [ ]: # MDP Environment
         import random
         class MDP(object):
           def init (self,Questions,Prob Rewards):
             self.Questions = Questions
            self.Prob_Rewards = Prob_Rewards
           def InitState(self):
             return 1
           def EndState(self, state):
             return state == self.Questions
           def Actions(self,state):
            if self.EndState(state):
               return []
            else:
               return ['Stay','Quit']
           def SuccProbReward(self, state, action):
            if action == 'Stay':
               if state > self.Questions:
                 return [(state,1.,0.)]
               else:
                 Probability = self.Prob Rewards[state][0]
                 Reward = self.Prob_Rewards[state][1]
                 return [(state+1,Probability,Reward),(self.Questions+1, 1.-Probability, 0.)
            elif action == 'Quit':
               if state > self.Questions:
                 return[(state,1.,0.)]
               else:
                 Probability = 1.0
                 Reward = self.Prob_Rewards[state][1]
                 return [(self.Questions+1, Probability, Reward)]
           def discount(self):
                 return 0.9
           def states(self):
             return range(1,self.Questions+2)
         # Value Iteration for the above Defined MDP environment
         def valueIteration(mdp, epsilon=0.001):
            # initialize values of all states to zero
            V = {s: 0.0 for s in mdp.states()}
            # repeat until convergence
            while True:
                 # set change to zero
                 delta = 0
                 # for each state, update its value using Bellman update
                 for s in mdp.states():
                     if mdp.EndState(s):
                         continue
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# compute the maximum value over all possible Actions
            MaxValue = -float('inf')
            for a in mdp.Actions(s):
                val = 0
                for NextState, Probability, Reward in mdp.SuccProbReward(s, a):
                    val += Probability * (Reward + mdp.discount() * V[NextState])
                MaxValue = max(MaxValue, val)
            # update value of state
            delta = max(delta, abs(MaxValue - V[s]))
            V[s] = MaxValue
        # check for convergence
        if delta < epsilon:</pre>
            break
    # compute the optimal policy using the computed values
    for s in mdp.states():
        if mdp.EndState(s):
            pi[s] = None
        else:
            MaxValue = -float('inf')
            best action = None
            for a in mdp.Actions(s):
                val = 0
                for NextState, Probability, Reward in mdp.SuccProbReward(s, a):
                    val += Probability * (Reward + mdp.discount() * V[NextState])
                if val > MaxValue:
                    MaxValue = val
                    best action = a
            pi[s] = best action
    # return the computed values and policy
    return V, pi
Questions = 10
Prob_Rewards = \{1: (0.99, 100),
                2: (0.9, 500),
                3: (0.8, 1000),
                4: (0.7, 5000),
                5: (0.6, 10000),
                6: (0.5, 50000),
                7: (0.4, 100000),
                8: (0.3, 500000),
                9: (0.2, 1000000),
                10: (0.1, 5000000)}
kbc MDP = MDP(Questions,Prob Rewards)
V, P = valueIteration(kbc MDP)
# kbc_MDP.MonteCarlo(2)
print(V)
print(P)
{1: 26780.771381760005, 2: 29945.87136000001, 3: 36414.656, 4: 49464.799999999996,
5: 72960.0, 6: 124000.0, 7: 220000.0, 8: 500000.0, 9: 1000000.0, 10: 0.0, 11: 0.0}
{1: 'Stay', 2: 'Stay', 3: 'Stay', 4: 'Stay', 5: 'Stay', 6: 'Stay', 7: 'Stay', 8:
'Quit', 9: 'Quit', 10: None, 11: 'Stay'}
```

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In [ ]: # Policy Iteration for the above Defined MDP environment
        def policyIteration(mdp, epsilon=0.001):
            # initialize values of all states to zero
            V = {s: 0.0 for s in mdp.states()}
            # initialize policy arbitrarily
            pi = {s: mdp.Actions(s)[0] for s in mdp.states() if not mdp.EndState(s)}
            while True:
                 # policy evaluation step
                while True:
                    delta = 0
                    for s in mdp.states():
                         if mdp.EndState(s):
                             continue
                         # compute the value of the current policy for this state
                         val = 0
                         for NextState, Probability, Reward in mdp.SuccProbReward(s, pi[s]):
                             val += Probability * (Reward + mdp.discount() * V[NextState])
                         # update value of state
                         delta = max(delta, abs(val - V[s]))
                         V[s] = val
                     if delta < epsilon:</pre>
                         break
                 # policy improvement step
                 policy_stable = True
                 for s in mdp.states():
                     if mdp.EndState(s):
                         continue
                    old action = pi[s]
                     # find the best action using the updated values
                    MaxValue = -float('inf')
                     best action = None
                    for a in mdp.Actions(s):
                        val = 0
                         for NextState, Probability, Reward in mdp.SuccProbReward(s, a):
                             val += Probability * (Reward + mdp.discount() * V[NextState])
                         if val > MaxValue:
                             MaxValue = val
                             best action = a
                     # update policy
                     pi[s] = best_action
                     if old action != best action:
                         policy_stable = False
                 # check for convergence
                 if policy stable:
                     break
            # return the computed values and policy
            return V, pi
        Questions = 10
        Prob Rewards = \{1: (0.99, 100),
                         2: (0.9, 500),
                         3: (0.8, 1000),
                         4: (0.7, 5000),
                         5: (0.6, 10000),
```

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6: (0.5, 50000),
                        7: (0.4, 100000),
                        8: (0.3, 500000),
                        9: (0.2, 1000000),
                        10: (0.1, 5000000)}
        kbc MDP = MDP(Questions,Prob Rewards)
        V ,P = policyIteration(kbc_MDP)
        print(P)
        print(V)
        {1: 'Stay', 2: 'Stay', 3: 'Stay', 4: 'Stay', 5: 'Stay', 6: 'Stay', 7: 'Stay', 8:
        'Quit', 9: 'Quit', 11: 'Stay'}
        {1: 26780.771381760005, 2: 29945.87136000001, 3: 36414.656, 4: 49464.799999999996,
        5: 72960.0, 6: 124000.0, 7: 220000.0, 8: 500000.0, 9: 1000000.0, 10: 0.0, 11: 0.0}
In [ ]: # Sate
        def generateSARS(kbc_MDP, pi, num_sequences=1, max_steps=100):
            sequences = []
            for i in range(num sequences):
                state = kbc MDP.InitState()
                sequence = []
                for t in range(max steps):
                    if kbc MDP.EndState(state):
                        break
                    action = pi[state]
                    next states, probabilities, rewards = zip(*kbc MDP.SuccProbReward(state
                    next_state = random.choices(next_states, probabilities)[0]
                    reward = rewards[next_states.index(next_state)]
                    sequence.append((state, action, reward, next_state))
                    state = next state
                sequences.append(sequence)
            return sequences
        sequences = generateSARS(kbc_MDP, P, num_sequences=10, max_steps=10)
        for sequence in sequences:
            print(sequence)
            print("\n")
```

```
[(1, 'Stay', 100, 2), (2, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

```
[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 1000, 4), (4, 'Stay', 5000, 5), (5, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

```
[(1, 'Stay', 100, 2), (2, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

```
[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

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[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

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[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 1000, 4), (4, 'Stay', 5000, 5), (5, 'Stay', 10000, 6), (6, 'Stay', 50000, 7), (7, 'Stay', 100000, 8), (8, 'Qui t', 500000, 11), (11, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

```
[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
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[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 1000, 4), (4, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

```
[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 1000, 4), (4, 'Stay', 5000, 5), (5, 'Stay', 10000, 6), (6, 'Stay', 50000, 7), (7, 'Stay', 100000, 8), (8, 'Qui t', 500000, 11), (11, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]
```

[(1, 'Stay', 100, 2), (2, 'Stay', 500, 3), (3, 'Stay', 0.0, 11), (11, 'Stay', 0.0, 11)]

```
In [ ]: # Monto Carlo Environment for the above problem
import random
```

class MontoCarlo(object):

```
def __init__(self, Questions, Prob_Rewards):
    self.Questions = Questions
    self.Prob Rewards = Prob Rewards
def play(self, policy):
    # initialize variables
    state = self.InitState()
    done = False
    rewards = []
    # play until the game is over
    while not done:
        # choose an action according to the given policy
        action = policy(state)
        # take the action and observe the next state and reward
        next state, reward, done = self.SuccProbReward(state, action)[0]
        # store the reward
        rewards.append(reward)
        # update the current state
        state = next state
    # compute the cumulative rewards for each time step
    cumulative rewards = [sum(rewards[i:]) for i in range(len(rewards))]
    # create a list of (state, action, cumulative reward) tuples
    episodes = [(self.InitState(), None, 0)]
    for i in range(len(rewards)):
        episodes.append((i+1, policy(i+1), cumulative rewards[i]))
    return episodes
def InitState(self):
    return 1
def EndState(self, state):
    return state == self.Questions + 1
def Actions(self, state):
    if self.EndState(state):
        return []
    else:
        return ['Stay', 'Quit']
def SuccProbReward(self, state, action):
    if action == 'Stay':
        if state > self.Questions:
            return [(state, 0, True)]
        else:
            prob, reward = self.Prob Rewards[state]
            if random.random() <= prob:</pre>
                return [(state+1, reward, False)]
            else:
                return [(self.Questions+1, 0, True)]
    elif action == 'Ouit':
        if state > self.Questions:
            return [(state, 0, True)]
        else:
            reward = self.Prob_Rewards[state][1]
            return [(self.Questions+1, reward, True)]
```

```
def discount(self):
                                        return 0.9
                              def states(self):
                                        return range(1, self.Questions+2)
                    # define a random policy
                     def random policy(state):
                              actions = ['Stay', 'Quit']
                              return random.choice(actions)
                     # create a MontoCarlo environment
                     env = MontoCarlo(10, [(0.99, 100), (0.9, 500), (0.8, 1000), (0.7, 5000), (0.6, 10000),
                     # run a random policy for one episode
                     episode = env.play(random_policy)
                    # print the episode
                     print(episode)
                    [(1, None, 0), (1, 'Stay', 6500), (2, 'Quit', 6000), (3, 'Quit', 5000), (4, 'Qui
                    t', 0)]
In [ ]: import numpy as np
                    # Define the KBC game
                    Questions = 10
                     Prob_Rewards = [(0.99, 100), (0.9, 500), (0.8, 1000), (0.7, 5000), (0.6, 10000), (0.5, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.6, 10000), (0.
                     # # Create the transition matrix
                     num states = Questions + 1
                     num actions = 2
                    R = np.zeros(num_states).astype(int)
                    for s in range(num_states):
                              if s == num states - 1:
                                        R[s] = 0 \# end of game
                              else:
                                        R[s] = Prob Rewards[s][1]
                    # # Format the output of the transition matrix
                     P1 = np.array([[0.99, 0.01, 0, 0, 0, 0, 0, 0, 0, 0],
                                                            [0, 0.9, 0.1, 0, 0, 0, 0, 0, 0, 0],
                                                            [0, 0, 0.8, 0.2, 0, 0, 0, 0, 0, 0]
                                                            [0, 0, 0, 0.7, 0.3, 0, 0, 0, 0, 0, 0],
                                                            [0, 0, 0, 0, 0.6, 0.4, 0, 0, 0, 0]
                                                            [0, 0, 0, 0, 0, 0.5, 0.5, 0, 0, 0, 0],
                                                            [0, 0, 0, 0, 0, 0, 0.4, 0.6, 0, 0, 0],
                                                            [0, 0, 0, 0, 0, 0, 0, 0.3, 0.7, 0, 0],
                                                            [0, 0, 0, 0, 0, 0, 0, 0, 0.2, 0.8, 0],
                                                            [0, 0, 0, 0, 0, 0, 0, 0, 0, 0.1, 0.9],
                                                              [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1]])
                     print("Transition matrix : \n")
```

```
for i in range(num_states):
    for j in range(num_states):
        print(P1[i][j], end = "
                                   ")
    print("\n")
print("Rewards Vector : \n")
print(R)
# Set up the discount factor
gamma = 0.9
# Solve the system of linear equations
A = np.eye(num_states) - gamma * P1
V = np.linalg.inv(A).dot(b) # value function
# Print the value function vector
print("\n Value function : \n")
print(V)
Transition matrix:
0.99
       0.01
              0.0
                          0.0
                                 0.0
                                       0.0
                                                   0.0
                                                          0.0
                                                                0.0
                    0.0
                                             0.0
0.0
      0.9
            0.1
                  0.0
                         0.0
                               0.0
                                     0.0
                                           0.0
                                                 0.0
                                                        0.0
                                                              0.0
0.0
      0.0
            0.8
                  0.2
                         0.0
                               0.0
                                     0.0
                                           0.0
                                                 0.0
                                                        0.0
                                                              0.0
0.0
      0.0
            0.0
                  0.7
                         0.3
                               0.0
                                     0.0
                                           0.0
                                                 0.0
                                                        0.0
                                                              0.0
      0.0
            0.0
                  0.0
                        0.6
                              0.4
                                     0.0
                                           0.0
                                                 0.0
                                                        0.0
                                                              0.0
0.0
0.0
      0.0
            0.0
                  0.0
                         0.0
                               0.5
                                     0.5
                                           0.0
                                                 0.0
                                                        0.0
                                                              0.0
0.0
      0.0
            0.0
                  0.0
                         0.0
                               0.0
                                     0.4
                                           0.6
                                                 0.0
                                                        0.0
                                                              0.0
      0.0
            0.0
                  0.0
                        0.0
                              0.0
                                     0.0
                                           0.3
                                                 0.7
                                                        0.0
                                                              0.0
0.0
0.0
      0.0
            0.0
                  0.0
                         0.0
                               0.0
                                     0.0
                                           0.0
                                                 0.2
                                                        0.8
                                                              0.0
0.0
      0.0
            0.0
                  0.0
                         0.0
                               0.0
                                     0.0
                                           0.0
                                                 0.0
                                                        0.1
                                                              0.9
0.0
      0.0
            0.0
                  0.0
                         0.0
                               0.0
                                     0.0
                                           0.0
                                                 0.0
                                                        0.0
                                                              1.0
Rewards Vector:
     100
             500
                    1000
                             5000
                                    10000
                                            50000 100000 500000 1000000
 5000000
               0]
 Value function :
63648.10943705 759738.21429313 1598336.23017438 2480745.24693792
 3381021.26432234 4292416.05996743 5135175.18440464 5900948.36670179
```

0.

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6043956.04395604 5494505.49450549

In []