## inventory beer game implementation

August 18, 2023

### 1 Reinforcement Learning Project - Inventory beer game

```
[]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import random
import sys
```

### 1.0.1 Setup

For better understanding of the code output decrease supply chain from customer to distributor, set  $max\_iteration$  to one, set lead time lag to False (line 25 in main function), activate print functions (main function) and define state- and action-pairs as follows: - state $\_pairs = [(i, j) \text{ for } i \text{ in states}]$  for j in states] - action $\_pairs = [(i, j) \text{ for } i \text{ in actions for } j \text{ in actions}]$ 

```
[]: # Supply Chain and its agents
     supply_chain = {'level 0': 'Customer',
                     'level 1': 'Retailer',
                     'level 2': 'Distributor',
                     'level 3': 'Manufacturer'}
     agents = [supply_chain[i] for i in list(supply_chain.keys())[1:]]
     # All possible coded inventory positions of agents and the respective state.
     ⇔pairs (5 states with 25 state pairs)
     states = np.arange(start=1, stop=7)
     state_pairs = [(i, j, k) for i in states for j in states for k in states]
     # y-value in ordering rule x+y with x equal to the demand from the downstream,
      sagent and the respective action pairs (4 actions with 16 action pairs)
     actions = np.arange(stop=4)
     action_pairs = [(i, j, k) for i in actions for j in actions for k in actions]
     # Initial matrix with Q-values (minimization -> high values)
     Q_values = np.full(shape=(len(state_pairs), len(action_pairs)), fill_value=1000)
```

```
display(df_Q_values.head())
                (0, 0, 0)
                                        (0, 0, 2)
                                                   (0, 0, 3)
                                                               (0, 1, 0)
                                                                           (0, 1, 1)
                            (0, 0, 1)
                                                         1000
                                                                     1000
                                                                                1000 \
    (1, 1, 1)
                     1000
                                 1000
                                             1000
    (1, 1, 2)
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    (1, 1, 3)
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                                                         1000
                                                                     1000
                                                                                1000
                                 1000
    (1, 1, 4)
                     1000
                                 1000
                                             1000
                                                         1000
                                                                     1000
                                                                                1000
    (1, 1, 5)
                     1000
                                 1000
                                             1000
                                                         1000
                                                                     1000
                                                                                1000
                (0, 1, 2)
                            (0, 1, 3)
                                        (0, 2, 0)
                                                   (0, 2, 1)
                                                               ... (3, 1, 2)
    (1, 1, 1)
                     1000
                                 1000
                                             1000
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                                                                        1000
    (1, 1, 2)
                     1000
                                 1000
                                             1000
                                                         1000 ...
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    (1, 1, 3)
                     1000
                                 1000
                                             1000
                                                         1000 ...
                                                                        1000
    (1, 1, 4)
                                                         1000 ...
                                                                        1000
                     1000
                                 1000
                                             1000
    (1, 1, 5)
                     1000
                                 1000
                                             1000
                                                         1000 ...
                                                                        1000
                (3, 1, 3)
                            (3, 2, 0)
                                        (3, 2, 1)
                                                   (3, 2, 2)
                                                               (3, 2, 3)
                                                                           (3, 3, 0)
    (1, 1, 1)
                     1000
                                 1000
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                                                                     1000
                                                                                1000 \
    (1, 1, 2)
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    (1, 1, 3)
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                                             1000
                                                         1000
                                                                     1000
                                                                                1000
    (1, 1, 4)
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                                                                                1000
    (1, 1, 5)
                     1000
                                 1000
                                             1000
                                                         1000
                                                                     1000
                                                                                1000
                (3, 3, 1)
                            (3, 3, 2)
                                        (3, 3, 3)
    (1, 1, 1)
                     1000
                                 1000
                                             1000
    (1, 1, 2)
                                             1000
                     1000
                                 1000
    (1, 1, 3)
                                 1000
                                             1000
                     1000
    (1, 1, 4)
                     1000
                                 1000
                                             1000
    (1, 1, 5)
                     1000
                                 1000
                                             1000
    [5 rows x 64 columns]
[]: # Define parameters
     iteration = 1
     max iteration = 100000 #1000000
     T = 10
     gamma = 0.9 #low: faster convergence! less variance
     alpha = 0.17 #high: faster updating q-values (more weight to new observations)
      ⇔and big variance in q-value updates
     sigma = 0.001
     proba exploitation = 0.02
     start_exploitation = proba_exploitation
     # Set up Lists to store the results of each iteration/episode
     S = [list(np.repeat(0, len(agents))) for i in range(T+4)]
```

df\_Q\_values = pd.DataFrame(data=Q\_values, index=state\_pairs,\_

⇔columns=action\_pairs)

```
CS = [list(np.repeat(0, len(agents))) for i in range(T+4)]
D = [list(np.repeat(0, len(agents))) for i in range(T+4)]
O = [list(np.repeat(0, len(agents))) for i in range(T+4)]
x = [list(np.repeat(0, len(agents))) for i in range(T+4)]
y = [list(np.repeat(0, len(agents))) for i in range(T+4)]
r = [list(np.repeat(0, len(agents))) for i in range(T+4)]
R = [0 for i in range(T)]
G = [0 for i in range(T)]
Q = [0 for i in range(max_iteration)]
```

Meaning of the variables - S: (start-)inventory positions/states per agent and time step t - CS: coded states per agent and time step t - O: ordering size per agent and time step t - D: distribution amount per agent and time step t - x: demand from downstream level per agent and time step t - y: action per agent and time step t - r: reward per agent and time step t - R: reward of the supply chain per time step t - Return G: total discounted rewards per time step t - q: measure the decrease of the Q-value per time step t - Q: measure the mean decrease of Q-values per episode to indicate convergence

```
[]: # helperfunctions
     # function to convert real states to coded states
     def coded_state(inventory):
         if inventory < -5:
             return 1
         elif inventory < 0:</pre>
             return 2
         elif inventory < 5:</pre>
             return 3
         elif inventory < 10:</pre>
             return 4
         elif inventory < 15:</pre>
             return 5
         else:
             return 6
     # function to view episodes
     def fun_episode(S, CS, D, O, x, y, r, head=True):
         time_steps = ['t='+str(i) for i in np.arange(start=0, stop=T+4)]
         df = pd.DataFrame({'Inventory/States S': [tuple(i) for i in S],
                         'Coded states CS': [tuple(i) for i in CS],
                         'Demand x': [tuple(i) for i in x],
                         'Distribution amount D': [tuple(i) for i in D],
                         'Action y': [tuple(i) for i in y],
                         'Ordering size': [tuple(i) for i in 0],
                         'Costs r': [tuple(i) for i in r]},
```

```
index=time_steps)
    df.index.name = 'Time'
    if head == True:
        return display(df.head())
    else: return display(df)
# function to define the starting states of the supply chain
def fun start state(how='value', inv=10):
    # select own start values for all agents
    if how == 'value':
        for agent in range(len(agents)):
            S[0][agent] = inv
            CS[0][agent] = coded_state(S[0][agent])
    # each episode has a change of 50% to start with high (12) or with low (0)_{\sqcup}
 ⇒inventory for all agents
    elif how == 'high/low':
        starting_state = random.choices(population=['high', 'low'], weights=[0.
 5, 0.5)[0]
        if starting_state == 'high':
            for agent in range(len(agents)):
                S[0][agent] = 10
                CS[0][agent] = coded_state(S[0][agent])
        else:
            for agent in range(len(agents)):
                S[0][agent] = 1
                CS[0][agent] = coded_state(S[0][agent])
    # random starting positions (-10 to 16) of agents for each episode
    elif how == 'random':
        for agent in range(len(agents)):
            S[0][agent] = random.choices(np.arange(start=-10, stop=16))[0]
            CS[0][agent] = coded state(S[0][agent])
# function to switch lead time lags on or off
def fun_lead_time(lag):
    if lag == False:
        lag = 0
    else: lag = random.choices(population=[0, 1, 2, 3, 4], weights=[0.3, 0.25, 0.25]
 90.2, 0.15, 0.1])[0]
    return lag
# function to measure the Q-value decrease
def fun_q_decrease(alpha, q_value, G):
```

```
new_q_value = (1-alpha) * q_value + alpha * G
         decrease = (q_value - new_q_value) / q_value
         return new_q_value, decrease
     # function to visualize the Q-vlaue decrease
     def plot_q_decrease(Q, iteration):
         plt.figure(figsize=(12,4))
         plt.plot(Q)
         plt.xlim(0, iteration)
         plt.ylim(-0.1, 1.1)
         plt.xlabel('episode/iteration')
         plt.ylabel('Q-value decrease')
         plt.title('Q-value decrease per episode', size=18)
         return plt.show()
[]: # Three possible options to set starting states
     fun_start_state(how='value', inv=10)
     print('Inventory state S: {}'.format(S))
     print('Coded state S: {}\n'.format(CS))
     fun start state(how='high/low')
     print('Inventory state S: {}'.format(S))
     print('Coded state S: {}\n'.format(CS))
     fun start state(how='random')
     print('Inventory state S: {}'.format(S))
     print('Coded state S: {}\n'.format(CS))
    Inventory state S: [[10, 10, 10], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0],
    [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0]
    0, 0], [0, 0, 0]]
    Coded state S: [[5, 5, 5], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0,
    0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0],
    [0, 0, 0]]
    Inventory state S: [[1, 1, 1], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0,
    0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0,
    0], [0, 0, 0]]
    Coded state S: [[3, 3, 3], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0]
    0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0],
    [0, 0, 0]
    Inventory state S: [[4, 0, -8], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0,
    0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0,
    0], [0, 0, 0]]
    Coded state S: [[3, 3, 1], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0,
    0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0], [0, 0, 0],
```

```
[]: #%%capture
    # Main function
    while iteration <= max_iteration:</pre>
        if iteration in [1, 10, 100, 1000, 10000, 25000, 50000, 75000,
                       100000, 250000, 500000, 750000, max iteration]:
             print('iteration {}'.format(iteration))
        #print('----'.format(iteration))
        #print('Exploitation probability: {}\n'.format(proba exploitation))
        # random starting position of agents for each episode
        fun_start_state(how='high/low') #option 1: ('value', inv=10); option 2:
      → 'high/low'; option 3: 'random'
        while t < T:
            \#print('-----'.format(t))
            # view state and coded state
            state = tuple(S[t])
            c_state = tuple(CS[t])
            #print('State S: {} and coded state CS: {}'.format(state, c_state))
            lead_time_lag = fun_lead_time(lag=True)
            #print('Lead time lag of {} time steps\n'.format(lead_time_lag))
            for agent in range(len(agents)):
                level = supply_chain['level ' + str(agent+1)]
                #print('----'.format(level))
            # step 1: receive the new demand of the downstream agent
                if level == 'Retailer':
                   x[t][agent] = np.random.randint(low=0, high=15)
                else:
                   x[t][agent] = 0[t-1][agent-1]
                # Add negative inventory (=demand of previous time steps) to the
     ⇒new demand
                inventory = S[t][agent]
                if inventory >= 0:
                   \#print('Demand\ x\ from\ downstream\ (\{\})\ at\ t-1:\ \{\}'.
     \neg format(supply\_chain['level ' + str(agent)], x[t][agent]))
                   pass
```

```
else:
               #print('Demand x from downstream ({}) at t-1 + demand of
⇒previous time steps:'.format(supply_chain['level ' + str(agent)]))
               \#print( '\{\} + \{\} = \{\}'.format(x[t][agent], np.
\Rightarrowabs(inventory), x[t][agent] + np.abs(inventory)))
               x[t][agent] += np.abs(inventory)
       # step 2: fulfill order of downstream agent from onhand inventory and
→calculate possible backlog costs
           # set lead time lags for all agents except retailer (lead time to,,
⇔customer is zero)
           if (level == agents[0]): lag = 0 #no lags in last iteration
           else: lag = lead_time_lag
           if (inventory >= 0) & (level != agents[-1]):
               D[t+lag][agent] += min(x[t][agent], max(inventory,
\rightarrowD[t-1][agent+1])) #distribution quantity is the demand or the maximum of
⇒inventory and last received order
               #print('Distribution size D in t={}: {}'.format(t+lag,__
\hookrightarrow D[t+lag][agent]))
           elif level != agents[-1]:
               D[t+lag][agent] += min(x[t][agent], D[t-1][agent+1]) #negative_
inventory is demand of previous time steps and still needs to be complied
               #print('Distribution size D (delivery of upstream agent in t-1)
\rightarrow in t={}: {}'.format(t+lag, D[t+lag][agent])) #(max of demand and last_
⇔received order)
           elif (inventory >= 0) & (level == agents[-1]):
               →O[t-1][agent])) #last agent receives his own order out of warehouse
               #print('Distribution size D in t=\{\}: \{\}'.format(t+lag, \bot
\hookrightarrow D[t+lag][agent]))
           else:
               D[t+lag][agent] += min(x[t][agent], 0[t-1][agent])
               #print('Distribution size D (delivery of warehouse) in t=\{\}:
\hookrightarrow {}'.format(t+lag, D[t+lag][agent]))
           backlog = max(0, x[t][agent] - D[t+lag][agent]) #penalty/backlog_
→costs (previous backlogs included in demand if inventory is negative)
           #print('Backlog size: {}'.format(backlog))
       # step 3: placing order for stock replenishment
           # define best action for agent and select it with initially very
⇔small probability (first exploration and mostly random choices)
           best_action = df_Q_values.iloc[df_Q_values.index.

¬get_loc(tuple(CS[t]))].idxmin()[agent]
           #print('Best action y*: {}'.format(best_action))
```

```
y[t][agent] = random.choices([best_action] + list(actions),__
weights=[proba_exploitation] + list(np.repeat((1 - proba_exploitation) / ___
→len(actions), len(actions))))[0]
           #print('Action y: {}'.format(y[t][agent]))
           if inventory >= 0:
               O[t][agent] = x[t][agent] + y[t][agent]
           else: O[t][agent] = x[t][agent] + inventory + y[t][agent] #subtractu
→negative inventory (demand of previous time steps) again - has been ordered
\hookrightarrow already
           #print('Ordering size O: {}\n'.format(O[t][agent]))
       # step 4: previous orders are received from the upstream agent (update_{\sqcup}
\hookrightarrow states for t+1)
       #print('UPDATING STATES AND CALCULATING COSTS PER AGENT')
       for agent in range(len(agents)):
           level = supply_chain['level ' + str(agent+1)]
           #print('----'.format(level))
           # update inventory with demand of t
           if S[t][agent] >= 0:
               inventory = S[t][agent] - x[t][agent]
           else: inventory = - x[t][agent] #demand x contains negative_
⇒inventory + new demand = new inventory
           # update state t+1 with inventory + received order
           if level != agents[-1]:
               S[t+1][agent] = inventory + D[t+lag][agent+1]
               #print('Inventory \{\} after receiving order +\{\} of t-1: \{\}'.
\hookrightarrow format(inventory, D[t][agent+1], S[t+1][agent]))
           # for last agent in supply chain: update state t+1 with inventory t_{-1}
\rightarrow order of t-1 (delivers from warehouse)
           else:
               S[t+1][agent] = inventory + O[t-1][agent]
               #print('Inventory \{\} receiving order +\{\} of t-1: \{\}'.
\hookrightarrow format(inventory, O[t-1][agent], S[t+1][agent]))
           # update coded states
           CS[t+1][agent] = coded_state(S[t+1][agent])
           # calculate agent's costs (onhand inventory holding costs + penalty_
⇔costs)
           r[t][agent] = 1 * max(S[t+1][agent], 0) + 2 * (x[t][agent] - 
→D[t][agent]) #backlog
```

```
\#print('Costs\ r:\ \{\}\n'.format(r[t][agent]))
       # calculate the total supply chain costs in t
       action = tuple(y[t])
       R[t] = np.sum(r[t])
       \#print('Supply\ Chain\ costs\ R\ in\ state\ \{\}\ with\ action\ \{\}\ at\ t=\{\}'.
\hookrightarrow format(state, action, t, R[t]))
       # increase time step t
      t += 1
       #print(' \n \n')
   # view last episode
   \#fun\_episode(S, CS, D, O, x, y, r, head=False)
  \# Loop from T to t=0 to calculate immediate rewards and returns
  #print('----Rewards and Total discounted returns-----')
  for t in np.arange(start=0, stop=T)[::-1]:
       # view immediate reward of each visited state-action-pair
       \#print('Immediate\ reward\ R\ in\ t=\{\}:\ \{\}'.format(t,\ R[t]))
       # calculate the return G: total discounted rewards
       G[t] = R[t] + np.sum(R[t+1:] * np.array([gamma**i for i in np.
⇒arange(start=1, stop=T-t)]))
  # view returns of all state-action-pairs
   \#print(' \setminus Total \ discounted \ rewards \ (Return \ G): \setminus n\{\} \setminus n'. format(G)\}
   # update all visited Q-values
  #print('-----')
  for t in range(T):
      state = tuple(CS[t])
      action = tuple(y[t])
       # get current Q-value
       q_value = df_Q_values.iloc[df_Q_values.index.get_loc(state),__
→df_Q_values.columns.get_loc(action)]
       #print('t={}: state: {}, action: {}, old Q-value: {}, return: {}'.
\hookrightarrow format(t, state, action, q_value, G[t]))
       # update Q-values according to equation 12 in the paper (slide 30_{\sqcup}
→ TD-learning script)
       df_Q_values.iloc[df_Q_values.index.get_loc(state), df_Q_values.columns.
Get_loc(action)] = (1-alpha) * q_value + alpha * G[t] #equal to: q_value + d
\Rightarrow alpha * (G[t] - q_value)
      new_q_value, decrease = fun_q_decrease(alpha, q_value, G[t])
```

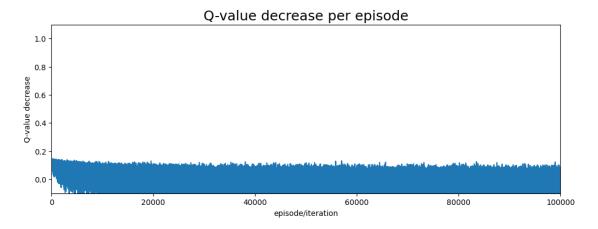
```
q[t] = decrease
         #print('New Q-value: {}\n'.format(new_q_value))
    # calculate mean Q-value decrease of current episode
    Q[iteration-1] = np.mean(q)
    #print('Mean Q-value decrease of all visited state-action-pairs in this
  →episode: {}'.format(Q[iteration-1]))
    # Check if the convergence criterion has been reached
    if (iteration > 100) & (np.mean(np.abs(Q[iteration-5:iteration])) < sigma):
        print('Convergence!')
        break
    # Set list D to zero again
    D = [list(np.repeat(0, len(agents))) for i in range(T+4)]
    # increase exploitation probability linearly
    proba_exploitation += (0.95 - start_exploitation) / max_iteration
    #print(' \n \n')
    # start with next iteration
    iteration += 1
# round dataframe with Q-values
df_Q_values = np.round(df_Q_values, 2)
# view new Q-value table
display(df_Q_values)
# plot decrease of Q-vlaues
plot_q_decrease(Q, iteration)
iteration 1
iteration 10
iteration 100
iteration 1000
iteration 10000
iteration 25000
iteration 50000
iteration 75000
iteration 100000
/anaconda/envs/jupyter_env/lib/python3.8/site-
packages/numpy/core/fromnumeric.py:3432: RuntimeWarning: Mean of empty slice.
 return _methods._mean(a, axis=axis, dtype=dtype,
/anaconda/envs/jupyter_env/lib/python3.8/site-
packages/numpy/core/_methods.py:190: RuntimeWarning: invalid value encountered
in double_scalars
```

ret = ret.dtype.type(ret / rcount)

	(0, 0, 0)	(0, 0, 1)	(0, 0, 2)	(0, 0, 3)	(0, 1, 0)	(0, 1, 1)	
(1, 1, 1)		552.42			566.56		
	475.17					546.49	
(1, 1, 3)			552.33				
(1, 1, 4)			340.74		360.80		
					288.51		
						333122	
(6, 6, 2)		365.03		242.08		828.30	
(6, 6, 3)			189.97		200.01		
(6, 6, 4)			203.87		191.64		
(6, 6, 5)			180.77		173.97		
(6, 6, 6)				143.86	149.97		
(0, 0, 0)	110.00	110.00	102.01	110.00	110.01	100.00	
	(0, 1, 2)	(0, 1, 3)	(0, 2, 0)	(0, 2, 1)	(3, 1,	2)	
(1, 1, 1)					538.		
(1, 1, 2)	504.62	496.64	498.18	504.20	498.	83	
					<b></b> 556.		
	344.45				366.		
		568.99					
	•••						
(6, 6, 2)		263.46		213.44		97	
(6, 6, 3)		189.78					
(6, 6, 4)			205.57				
(6, 6, 5)	186.04	1//.43	159.42	229.55	1/4.	48	
(6, 6, 5) (6, 6, 6)				229.55 148.24			
(6, 6, 6)				148.24			
	189.83	140.54	150.28	148.24		21	
(6, 6, 6)	189.83	140.54	150.28 (3, 2, 1)	148.24	170.	21 (3, 3, 0)	
(6, 6, 6) (1, 1, 1)	189.83 (3, 1, 3) 535.68	140.54 (3, 2, 0) 587.73	150.28 (3, 2, 1) 626.04	148.24 (3, 2, 2) 562.00	170. (3, 2, 3) 535.52	21 (3, 3, 0) 542.30	
(6, 6, 6) (1, 1, 1) (1, 1, 2)	189.83	140.54 (3, 2, 0) 587.73 523.50	150.28 (3, 2, 1) 626.04 516.35	148.24 (3, 2, 2) 562.00 501.66	170.	21 (3, 3, 0) 542.30 508.24	
(6, 6, 6) (1, 1, 1) (1, 1, 2) (1, 1, 3)	189.83 (3, 1, 3) 535.68 486.54 574.24	140.54 (3, 2, 0) 587.73 523.50 538.40	150.28 (3, 2, 1) 626.04 516.35 567.50	148.24 (3, 2, 2) 562.00 501.66 573.71	170. (3, 2, 3) 535.52 513.96	21 (3, 3, 0) 542.30 508.24 556.46	
(6, 6, 6) (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4)	189.83 (3, 1, 3) 535.68 486.54 574.24 375.30	140.54 (3, 2, 0) 587.73 523.50 538.40 342.99	150.28 (3, 2, 1) 626.04 516.35 567.50 344.38	148.24 (3, 2, 2) 562.00 501.66 573.71 359.95	170. (3, 2, 3) 535.52 513.96 527.94	21 (3, 3, 0) 542.30 508.24 556.46 345.27	
(6, 6, 6) (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4)	189.83 (3, 1, 3) 535.68 486.54 574.24 375.30	140.54 (3, 2, 0) 587.73 523.50 538.40 342.99 293.03	150.28 (3, 2, 1) 626.04 516.35 567.50 344.38	148.24 (3, 2, 2) 562.00 501.66 573.71 359.95 579.99	170. (3, 2, 3) 535.52 513.96 527.94 376.52	21 (3, 3, 0) 542.30 508.24 556.46 345.27	
(6, 6, 6) (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4)	189.83 (3, 1, 3) 535.68 486.54 574.24 375.30 364.00	140.54 (3, 2, 0) 587.73 523.50 538.40 342.99 293.03	150.28 (3, 2, 1) 626.04 516.35 567.50 344.38 697.77	148.24 (3, 2, 2) 562.00 501.66 573.71 359.95 579.99	170.  (3, 2, 3) 535.52 513.96 527.94 376.52 765.03	21 (3, 3, 0) 542.30 508.24 556.46 345.27	
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(1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4) (1, 1, 5)  (6, 6, 2)	189.83 (3, 1, 3) 535.68 486.54 574.24 375.30 364.00 425.61	140.54 (3, 2, 0) 587.73 523.50 538.40 342.99 293.03 192.17	150.28 (3, 2, 1) 626.04 516.35 567.50 344.38 697.77 278.86 215.54	148.24 (3, 2, 2) 562.00 501.66 573.71 359.95 579.99 313.72	170.  (3, 2, 3) 535.52 513.96 527.94 376.52 765.03 213.58	21 (3, 3, 0) 542.30 508.24 556.46 345.27 269.14 226.80	
(6, 6, 6) (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4) (1, 1, 5)  (6, 6, 2) (6, 6, 3)	189.83 (3, 1, 3) 535.68 486.54 574.24 375.30 364.00 425.61 219.49	140.54  (3, 2, 0) 587.73 523.50 538.40 342.99 293.03 192.17 209.75	150.28 (3, 2, 1) 626.04 516.35 567.50 344.38 697.77 278.86 215.54	148.24 (3, 2, 2) 562.00 501.66 573.71 359.95 579.99 313.72 186.22	170.  (3, 2, 3) 535.52 513.96 527.94 376.52 765.03 213.58 211.97	21 (3, 3, 0) 542.30 508.24 556.46 345.27 269.14 226.80 236.76	
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(6, 6, 6) (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4) (1, 1, 5)  (6, 6, 2) (6, 6, 3) (6, 6, 4) (6, 6, 5)	189.83 (3, 1, 3) 535.68 486.54 574.24 375.30 364.00 425.61 219.49 184.25 163.09	140.54  (3, 2, 0) 587.73 523.50 538.40 342.99 293.03 192.17 209.75 183.07 178.95	150.28  (3, 2, 1) 626.04 516.35 567.50 344.38 697.77 278.86 215.54 185.96 188.98	148.24  (3, 2, 2) 562.00 501.66 573.71 359.95 579.99 313.72 186.22 185.52 172.59	170.  (3, 2, 3) 535.52 513.96 527.94 376.52 765.03 213.58 211.97 209.05 174.38	21 (3, 3, 0) 542.30 508.24 556.46 345.27 269.14  226.80 236.76 199.19 188.71	
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(6, 6, 6)  (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4) (1, 1, 5) (6, 6, 2) (6, 6, 3) (6, 6, 4) (6, 6, 6) (1, 1, 1)	189.83 (3, 1, 3) 535.68 486.54 574.24 375.30 364.00 425.61 219.49 184.25 163.09 177.82	140.54  (3, 2, 0) 587.73 523.50 538.40 342.99 293.03 192.17 209.75 183.07 178.95 174.64	150.28  (3, 2, 1) 626.04 516.35 567.50 344.38 697.77 278.86 215.54 185.96 188.98 160.59	148.24  (3, 2, 2) 562.00 501.66 573.71 359.95 579.99 313.72 186.22 185.52 172.59	170.  (3, 2, 3) 535.52 513.96 527.94 376.52 765.03 213.58 211.97 209.05 174.38	21 (3, 3, 0) 542.30 508.24 556.46 345.27 269.14  226.80 236.76 199.19 188.71	
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(6, 6, 6)  (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4) (1, 1, 5) (6, 6, 2) (6, 6, 3) (6, 6, 4) (6, 6, 5) (6, 6, 6)  (1, 1, 1) (1, 1, 2)	189.83  (3, 1, 3) 535.68 486.54 574.24 375.30 364.00 425.61 219.49 184.25 163.09 177.82  (3, 3, 1) 544.11 549.12	140.54  (3, 2, 0) 587.73 523.50 538.40 342.99 293.03 192.17 209.75 183.07 178.95 174.64  (3, 3, 2) 537.64 523.13	150.28  (3, 2, 1) 626.04 516.35 567.50 344.38 697.77 278.86 215.54 185.96 188.98 160.59  (3, 3, 3) 532.39 556.65	148.24  (3, 2, 2) 562.00 501.66 573.71 359.95 579.99 313.72 186.22 185.52 172.59	170.  (3, 2, 3) 535.52 513.96 527.94 376.52 765.03 213.58 211.97 209.05 174.38	21 (3, 3, 0) 542.30 508.24 556.46 345.27 269.14  226.80 236.76 199.19 188.71	
(6, 6, 6)  (1, 1, 1) (1, 1, 2) (1, 1, 3) (1, 1, 4) (1, 1, 5) (6, 6, 2) (6, 6, 3) (6, 6, 4) (6, 6, 5) (6, 6, 6)  (1, 1, 1) (1, 1, 2) (1, 1, 3)	189.83  (3, 1, 3) 535.68 486.54 574.24 375.30 364.00 425.61 219.49 184.25 163.09 177.82  (3, 3, 1) 544.11 549.12 571.69	140.54  (3, 2, 0) 587.73 523.50 538.40 342.99 293.03 192.17 209.75 183.07 178.95 174.64  (3, 3, 2) 537.64 523.13 560.06	150.28  (3, 2, 1) 626.04 516.35 567.50 344.38 697.77  278.86 215.54 185.96 188.98 160.59  (3, 3, 3) 532.39 556.65 551.72	148.24  (3, 2, 2) 562.00 501.66 573.71 359.95 579.99 313.72 186.22 185.52 172.59	170.  (3, 2, 3) 535.52 513.96 527.94 376.52 765.03 213.58 211.97 209.05 174.38	21 (3, 3, 0) 542.30 508.24 556.46 345.27 269.14  226.80 236.76 199.19 188.71	

```
(6, 6, 2)
              711.26
                           388.32
                                       463.74
(6, 6, 3)
               200.87
                           193.93
                                       184.56
(6, 6, 4)
               192.08
                           188.18
                                       216.37
(6, 6, 5)
              207.22
                           197.14
                                       159.90
(6, 6, 6)
               143.16
                           147.92
                                       151.58
```

[216 rows x 64 columns]



### 1.0.2 View new Q-values

```
[]: # Percentage of updated Q-values
     num_pairs = len(df_Q_values.index) * len(df_Q_values.columns)
     print('Number of state-action-pairs: {}'.format(num_pairs))
     print('Percentage of updated Q-values: {} %\n'.format(np.round(np.sum(np.

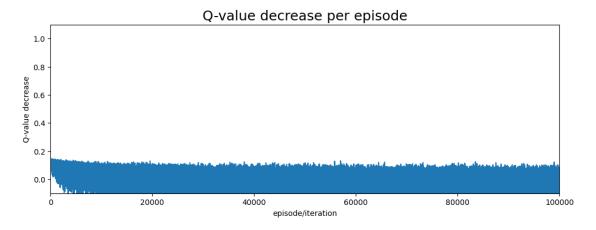
sum(df_Q_values != 10000)) / num_pairs * 100, 4)))
     visits = max iteration * T
     print('Number of visits with max_iteration={} and T={}: {}'.
      →format(max_iteration, T, visits))
     print('Average amount of visits per state-action-pair: {}\n'.format(np.
      →round(visits / num_pairs, 2)))
     # plot decrease of Q-vlaues
     print('Last five Q-value decreases: {}'.format(np.round(Q[iteration-5:
      →iteration], 4)))
     print('Mean of last five Q-value decreases: {}'.format(np.round(np.
      →mean(Q[iteration-5:iteration]), 4)))
     plot_q_decrease(Q, iteration)
     df_Q_values
```

Number of state-action-pairs: 13824 Percentage of updated Q-values: 100.0 %

Number of visits with max\_iteration=100000 and T=10: 1000000 Average amount of visits per state-action-pair: 72.34

Last five Q-value decreases: [  $0.0168 \ 0.0688 \ 0.0176 \ -0.0177$ ]

Mean of last five Q-value decreases: 0.0214



[]:		(0, 0, 0)	(0, 0, 1)	(0, 0, 2)	(0, 0, 3)	(0, 1, 0)	(0, 1, 1)	
	(1, 1, 1)	501.23	552.42	518.74	535.64	566.56	536.72	\
	(1, 1, 2)	475.17	532.60	493.29	490.40	512.01	546.49	
	(1, 1, 3)	560.06	555.98	552.33	551.08	546.45	546.47	
	(1, 1, 4)	348.59	339.97	340.74	369.41	360.80	367.38	
	(1, 1, 5)	266.57	323.55	300.17	455.90	288.51	398.12	
	•••	•••	•••		•••	•••		
	(6, 6, 2)	223.97	365.03	396.32	242.08	200.17	828.30	
	(6, 6, 3)	185.61	198.60	189.97	193.55	200.01	189.43	
	(6, 6, 4)	212.60	192.59	203.87	206.33	191.64	215.89	
	(6, 6, 5)	200.63	191.76	180.77	178.83	173.97	198.51	
	(6, 6, 6)	140.80	140.89	152.81	143.86	149.97	186.05	
		(0, 1, 2)	(0, 1, 3)	(0, 2, 0)	(0, 2, 1)	(3, 1, 2	2)	
	(1, 1, 1)	533.26	514.50	518.42	531.77	538.8	33 \	
	(1, 1, 2)	504.62	496.64	498.18	504.20	498.8	33	
	(1, 1, 3)	602.06	573.11	549.24	569.52	<b></b> 556.7	<b>'</b> 9	
	(1, 1, 4)	344.45	368.29	343.38	372.05	366.6	34	
	(1, 1, 5)	561.68	568.99	306.52	343.55	860.1	.5	
	•••	•••	•••		•••	•••		
	(6, 6, 2)	629.29	263.46	209.75	213.44	571.9	7	
	(6, 6, 3)	184.17	189.78	199.21	219.13	217.0	)3	
	(6, 6, 4)	196.29	206.44	205.57	185.04	199.8	31	

```
(6, 6, 5)
               186.04
                           177.43
                                       159.42
                                                   229.55 ...
                                                                  174.48
(6, 6, 6)
               189.83
                           140.54
                                       150.28
                                                   148.24
                                                                  170.21
                                    (3, 2, 1)
            (3, 1, 3)
                        (3, 2, 0)
                                                (3, 2, 2)
                                                           (3, 2, 3)
                                                                       (3, 3, 0)
(1, 1, 1)
               535.68
                           587.73
                                       626.04
                                                   562.00
                                                              535.52
                                                                           542.30
(1, 1, 2)
               486.54
                           523.50
                                       516.35
                                                  501.66
                                                              513.96
                                                                          508.24
(1, 1, 3)
                                                   573.71
                                                              527.94
               574.24
                           538.40
                                       567.50
                                                                          556.46
(1, 1, 4)
               375.30
                           342.99
                                       344.38
                                                   359.95
                                                              376.52
                                                                          345.27
(1, 1, 5)
               364.00
                           293.03
                                       697.77
                                                   579.99
                                                              765.03
                                                                          269.14
(6, 6, 2)
               425.61
                           192.17
                                       278.86
                                                   313.72
                                                              213.58
                                                                          226.80
(6, 6, 3)
               219.49
                           209.75
                                       215.54
                                                   186.22
                                                              211.97
                                                                          236.76
(6, 6, 4)
               184.25
                           183.07
                                       185.96
                                                   185.52
                                                              209.05
                                                                           199.19
(6, 6, 5)
               163.09
                           178.95
                                       188.98
                                                   172.59
                                                              174.38
                                                                           188.71
(6, 6, 6)
               177.82
                           174.64
                                       160.59
                                                   151.58
                                                              173.46
                                                                           157.79
            (3, 3, 1)
                       (3, 3, 2)
                                   (3, 3, 3)
(1, 1, 1)
               544.11
                           537.64
                                       532.39
(1, 1, 2)
               549.12
                           523.13
                                       556.65
(1, 1, 3)
               571.69
                           560.06
                                       551.72
(1, 1, 4)
               375.39
                           344.34
                                       364.03
(1, 1, 5)
                                       429.78
               272.63
                           367.33
(6, 6, 2)
               711.26
                           388.32
                                       463.74
(6, 6, 3)
               200.87
                           193.93
                                       184.56
(6, 6, 4)
               192.08
                           188.18
                                       216.37
(6, 6, 5)
                           197.14
               207.22
                                       159.90
(6, 6, 6)
                           147.92
               143.16
                                       151.58
```

[216 rows x 64 columns]

# 1.0.3 Test performance of the Reinforcement learning ordering mechanism (RLOM) on main and test problems

```
set2 = {'customer_demand':__
      \rightarrow [15,10,8,14,9,3,13,2,13,11,3,4,6,11,15,12,15,4,12,3,13,10,15,15,3,11,1,13,10,10,0,0,8,0,14]
             'lead_times':⊔
      4[4,2,2,0,2,2,1,1,3,0,0,3,3,3,4,1,1,1,3,0,4,2,3,4,1,3,3,3,0,3,4,3,3,0,3]]
     # Test problem 3
    set3 = {'customer_demand':_
      \rightarrow [13,13,12,10,14,13,13,10,2,12,11,9,11,3,7,6,12,12,3,10,3,9,4,15,12,7,15,5,1,15,11,9,14,0,4]
            'lead times':
     4[4,2,2,0,2,2,1,1,3,0,0,3,3,3,4,1,1,1,3,0,4,2,3,4,1,3,3,3,0,3,4,3,3,0,3]}
     # Own test problem
    set4 = {'customer_demand': list(np.random.randint(low=0, high=15, size=35)),
             'lead_times': list(np.random.randint(low=0, high=4, size=35))}
[]: def main_function(problem_set, policy, t=0, T=len(main_set['customer_demand'])):
         # set starting position of agents
        fun_start_state(how='value', inv=10)
        while t < T:
            print('----'.format(t))
            # view state and coded state
            state = tuple(S[t])
            c_state = tuple(CS[t])
            print('State S: {} and coded state CS: {}'.format(state, c_state))
            # define random lead time lag (between 0 and 4)
            lead_time_lag = problem_set['lead_times'][t]
            print('Lead time lag of {} time steps\n'.format(lead_time_lag))
            for agent in range(len(agents)):
                level = supply_chain['level ' + str(agent+1)]
                print('-----',format(level))
            # step 1: receive the new demand of the downstream agent
                if level == 'Retailer':
                    x[t][agent] = problem_set['customer_demand'][t]
                    x[t][agent] = 0[t-1][agent-1]
                # Add negative inventory (=demand of previous time steps) to the
      \rightarrownew demand
                inventory = S[t][agent]
                if inventory >= 0:
                    print('Demand x from downstream ({}) at t-1: {}'.

¬format(supply_chain['level ' + str(agent)], x[t][agent]))
```

```
else:
               print('Demand x from downstream ({}) at t-1 + demand of__
oprevious time steps:'.format(supply_chain['level ' + str(agent)]))
              print(
                       '{} + {} = {}'.format(x[t][agent], np.abs(inventory),
→x[t][agent] + np.abs(inventory)))
               x[t][agent] += np.abs(inventory)
       # step 2: fulfill order of downstream agent from onhand inventory and
⇔calculate possible backlog costs
           # set lead time lags for all agents except retailer (lead time to \Box
⇔customer is zero)
           if (level == agents[0]): lag = 0 #no lags in last iteration
           else: lag = lead_time_lag
           if (inventory >= 0) & (level != agents[-1]):
               D[t+lag][agent] = min(x[t][agent], max(inventory,
\rightarrowD[t-1][agent+1])) #distribution quantity is the demand or the maximum of
⇒inventory and last received order
               print('Distribution size D in t={}: {}'.format(t+lag, ⊔
→D[t+lag][agent]))
           elif level != agents[-1]:
               D[t+lag][agent] = min(x[t][agent], D[t-1][agent+1]) #negative_
inventory is demand of previous time steps and still needs to be complied
               print('Distribution size D (delivery of upstream agent in t-1)
→ in t={}: {}'.format(t+lag, D[t+lag][agent])) #(max of demand and last
⇔received order)
           elif (inventory >= 0) & (level == agents[-1]):
               D[t+lag][agent] = min(x[t][agent], max(inventory,
→O[t-1][agent])) #last agent receives his own order out of warehouse
              print('Distribution size D in t={}: {}'.format(t+lag,__
→D[t+lag][agent]))
           else:
               D[t+lag][agent] = min(x[t][agent], O[t-1][agent])
               print('Distribution size D (delivery of warehouse) in t={}: {}'.
→format(t+lag, D[t+lag][agent]))
           backlog = max(0, x[t][agent] - D[t+lag][agent]) #penalty/backlog_
→costs (previous backlogs included in demand if inventory is negative)
           print('Backlog size: {}'.format(backlog))
       # step 3: placing order for stock replenishment
           if policy == 'optimum':
               y[t][agent] = opt_policy[tuple(CS[t])][agent]
           elif policy == 'zero':
               y[t][agent] = 0
```

```
else: y[t][agent] = np.random.randint(4)
           print('Action y: {}'.format(y[t][agent]))
           if inventory >= 0:
               O[t][agent] = x[t][agent] + y[t][agent]
           else: O[t][agent] = x[t][agent] + inventory + y[t][agent] #subtract_
→negative inventory (demand of previous time steps) again - has been ordered
\hookrightarrowalready
          print('Ordering size 0: {}\n'.format(O[t][agent]))
       # step 4: previous orders are received from the upstream agent (update_
\hookrightarrow states for t+1)
      print('UPDATING STATES AND CALCULATING COSTS PER AGENT')
      for agent in range(len(agents)):
           level = supply_chain['level ' + str(agent+1)]
           print('-----'.format(level))
           # update inventory with demand of t
           if S[t][agent] >= 0:
               inventory = S[t][agent] - x[t][agent]
           else: inventory = - x[t][agent] #demand x contains negative_
⇒inventory + new demand = new inventory
           # update state t+1 with inventory + received order
           if level != agents[-1]:
               S[t+1][agent] = inventory + D[t+lag][agent+1]
              print('Inventory {} after receiving order +{} of t-1: {}'.
→format(inventory, D[t][agent+1], S[t+1][agent]))
           # for last agent in supply chain: update state t+1 with inventory +
\hookrightarrow order of t-1 (delivers from warehouse)
           else:
               S[t+1][agent] = inventory + O[t-1][agent]
               print('Inventory {} receiving order +{} of t-1: {}'.

¬format(inventory, O[t-1][agent], S[t+1][agent]))
           # update coded states
           CS[t+1][agent] = coded_state(S[t+1][agent])
           # calculate agent's costs (onhand inventory holding costs + penalty_
⇔costs)
          r[t][agent] = 1 * max(S[t+1][agent], 0) + 2 * (x[t][agent] - 0
→D[t][agent]) #backlog
           print('Costs r: {}\n'.format(r[t][agent]))
       # calculate the total supply chain costs in t
```

```
action = tuple(y[t])
R[t] = np.sum(r[t])
print('Supply Chain costs R in state {} with action {} at t={}: {}'.

oformat(state, action, t, R[t]))

# increase time step t
t += 1
print('\n\n')

# view episode
fun_episode(S, CS, D, O, x, y, r, head=False)

# View results
print(R)
print(np.sum(R))

return np.sum(R)
T = 35
```

```
# Set up Lists to store the results of each iteration/episode
S = [list(np.repeat(0, len(agents))) for i in range(T+4)]
CS = [list(np.repeat(0, len(agents))) for i in range(T+4)]
D = [list(np.repeat(0, len(agents))) for i in range(T+4)]
U = [0 for i in range(T)]

# Extract optimal policy of Q-values
U optimum_policy = []
U benchmark1 = []
U benchmark2 = []
```

```
optimum_policy.append(main_function(t=0, T=35, problem_set=set4, policy='optimum'))
```

### 1.0.4 Benchmark policy 1: Order = demand (y=0)

```
# Set up Lists to store the results of each iteration/episode
S = [list(np.repeat(0, len(agents))) for i in range(T+4)]
CS = [list(np.repeat(0, len(agents))) for i in range(T+4)]
D = [list(np.repeat(0, len(agents))) for i in range(T+4)]
O = [list(np.repeat(0, len(agents))) for i in range(T+4)]
x = [list(np.repeat(0, len(agents))) for i in range(T+4)]
y = [list(np.repeat(0, len(agents))) for i in range(T+4)]
r = [list(np.repeat(0, len(agents))) for i in range(T+4)]
R = [0 for i in range(T)]
```

```
benchmark1.append(main_function(problem_set=set1, policy='zero', t=0, T=35))
benchmark1.append(main_function(t=0, T=35, problem_set=set1, policy='zero'))
benchmark1.append(main_function(t=0, T=35, problem_set=set2, policy='zero'))
benchmark1.append(main_function(t=0, T=35, problem_set=set3, policy='zero'))
benchmark1.append(main_function(t=0, T=35, problem_set=set4, policy='zero'))
```

### 1.0.5 Benchmark policy 2: Order = demand + random y [0, 3]

```
# Set up Lists to store the results of each iteration/episode
S = [list(np.repeat(0, len(agents))) for i in range(T+4)]
CS = [list(np.repeat(0, len(agents))) for i in range(T+4)]
D = [list(np.repeat(0, len(agents))) for i in range(T+4)]
O = [list(np.repeat(0, len(agents))) for i in range(T+4)]
x = [list(np.repeat(0, len(agents))) for i in range(T+4)]
y = [list(np.repeat(0, len(agents))) for i in range(T+4)]
r = [list(np.repeat(0, len(agents))) for i in range(T+4)]
R = [0 for i in range(T)]
```

```
benchmark2.append(main_function(problem_set=set1, policy='random', t=0, T=35))
benchmark2.append(main_function(t=0, T=35, problem_set=set1, policy='random'))
benchmark2.append(main_function(t=0, T=35, problem_set=set2, policy='random'))
benchmark2.append(main_function(t=0, T=35, problem_set=set3, policy='random'))
benchmark2.append(main_function(t=0, T=35, problem_set=set4, policy='random'))
```

#### 1.0.6 Compare costs for all problem sets

```
[]: print('Sum of costs per problem of optimum policy with Q-vales lernt byRLOM:

¬\n{}'.format(optimum_policy))
     print('Mean costs: {}\n'.format(np.round(np.mean(optimum_policy))))
     print('Sum of costs per problem of benchmark1 (y=0):\n{}'.format(benchmark1))
     print('Mean costs: {}\n'.format(np.round(np.mean(benchmark1))))
     print('Sum of costs per problem of benchmark2 (random):\n{}'.format(benchmark2))
    print('Mean costs: {}\n'.format(np.round(np.mean(benchmark2))))
    Sum of costs per problem of optimum policy with Q-vales lernt byRLOM:
    [5287, 4356, 3569, 3629, 2298]
    Mean costs: 3828.0
    Sum of costs per problem of benchmark1 (y=0):
    [5903, 5903, 4519, 4608, 2978]
    Mean costs: 4782.0
    Sum of costs per problem of benchmark2 (random):
    [3698, 3712, 3907, 3806, 2247]
    Mean costs: 3474.0
```