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:

1.1

```{python}
1 + 1

2

1.2

11/30 12/5 12/12 12/19 12/26 1/2

book

```
 git wsl
 rstudio quarto
 https://github.com/Roku-3/rindoku_RL main rstudio
```

#### 1.3.1

```
git pull origin HEAD # github

git add . #

git commit -m "edit chapter 2" #

-m

git push origin HEAD # github

2 push

git branch main push

push
```

#### 1.3.2

github

2.0.1

197X

3 :

/

# 3.1

```
(policy)
(reward)
(value function)
(model)
```

0~1 0 1 0.5

 $V(s_t) \leftarrow V(s_t) + \alpha \left[ V\left(s_{t+1}\right) - V(s_t) \right]$ V(s) s TD; temporal-difference learning

```
self play
1.1
```{python}
    1 1 1
    import numpy as np
    import pickle
    111
'\nimport numpy as np\nimport pickle\n'
```{python}
 n n n
 BOARD_ROWS = 3
 BOARD_COLS = 3
 BOARD_SIZE = BOARD_ROWS * BOARD_COLS
 class State:
 def __init__(self):
 self.data = np.zeros((BOARD_ROWS, BOARD_COLS))
 self.winner = None
 self.hashVal = None
 self.end = None
```

```
def getHash(self):
 if self.hashVal is None:
 self.hashVal = 0
 for i in self.data.reshape(BOARD_ROWS * BOARD_COLS):
 if i == -1:
 i = 2
 self.hashVal = self.hashVal * 3 + i
 return int(self.hashVal)
def isEnd(self):
 if self.end is not None:
 return self.end
 results = []
 for i in range(0, BOARD_ROWS):
 results.append(np.sum(self.data[i, :]))
 for i in range(0, BOARD_COLS):
 results.append(np.sum(self.data[:, i]))
 results.append(0)
 for i in range(0, BOARD_ROWS):
 results[-1] += self.data[i, i]
 results.append(0)
 for i in range(0, BOARD_ROWS):
 results[-1] += self.data[i, BOARD_ROWS - 1 - i]
 for result in results:
 if result == 3:
 self.winner = 1
 self.end = True
 return self.end
 if result == -3:
 self.winner = -1
 self.end = True
 return self.end
 sum = np.sum(np.abs(self.data))
 if sum == BOARD ROWS * BOARD COLS:
 self.winner = 0
 self.end = True
 return self.end
 self.end = False
 return self.end
```

```
def nextState(self, i, j, symbol):
 newState = State()
 newState.data = np.copy(self.data)
 newState.data[i, j] = symbol
 return newState
 # print board
 def show(self):
 for i in range(0, BOARD_ROWS):
 print('----')
 out = '/'
 for j in range(0, BOARD_COLS):
 if self.data[i, j] == 1:
 token = '*'
 if \ self.data[i, j] == 0:
 token = '0'
 if \ self. data[i, j] == -1:
 token = 'x'
 out += token + ' / '
 print(out)
 print('----')
def qetAllStatesImpl(currentState, currentSymbol, allStates):
 for i in range(0, BOARD_ROWS):
 for j in range(0, BOARD_COLS):
 if currentState.data[i][j] == 0:
 newState = currentState.nextState(i, j, currentSymbol)
 newHash = newState.getHash()
 if newHash not in allStates.keys():
 isEnd = newState.isEnd()
 allStates[newHash] = (newState, isEnd)
 if not isEnd:
 getAllStatesImpl(newState, -currentSymbol, allStates)
def getAllStates():
 currentSymbol = 1
 currentState = State()
 allStates = dict()
 allStates[currentState.getHash()] = (currentState, currentState.isEnd())
 getAllStatesImpl(currentState, currentSymbol, allStates)
 return allStates
```

```
allStates = getAllStates()
class Judger:
 def __init__(self, player1, player2, feedback=True):
 self.p1 = player1
 self.p2 = player2
 self.feedback = feedback
 self.currentPlayer = None
 self.p1Symbol = 1
 self.p2Symbol = -1
 self.p1.setSymbol(self.p1Symbol)
 self.p2.setSymbol(self.p2Symbol)
 self.currentState = State()
 self.allStates = allStates
 def giveReward(self):
 if self.currentState.winner == self.p1Symbol:
 self.p1.feedReward(1)
 self.p2.feedReward(0)
 elif self.currentState.winner == self.p2Symbol:
 self.p1.feedReward(0)
 self.p2.feedReward(1)
 else:
 self.p1.feedReward(0.1)
 self.p2.feedReward(0.5)
 def feedCurrentState(self):
 self.p1.feedState(self.currentState)
 self.p2.feedState(self.currentState)
 def reset(self):
 self.p1.reset()
 self.p2.reset()
 self.currentState = State()
 self.currentPlayer = None
 def play(self, show=False):
 self.reset()
 self.feedCurrentState()
 while True:
 if self.currentPlayer == self.p1:
 self.currentPlayer = self.p2
 else:
```

```
self.currentPlayer = self.p1
 if show:
 self.currentState.show()
 [i, j, symbol] = self.currentPlayer.takeAction()
 self.currentState = self.currentState.nextState(i, j, symbol)
 hashValue = self.currentState.getHash()
 self.currentState, isEnd = self.allStates[hashValue]
 self.feedCurrentState()
 if isEnd:
 if self.feedback:
 self.giveReward()
 return self.currentState.winner
AI player
class Player:
 def __init__(self, stepSize = 0.1, exploreRate=0.1):
 self.allStates = allStates
 self.estimations = dict()
 self.stepSize = stepSize
 self.exploreRate = exploreRate
 self.states = []
 def reset(self):
 self.states = []
 def setSymbol(self, symbol):
 self.symbol = symbol
 for hash in self.allStates.keys():
 (state, isEnd) = self.allStates[hash]
 if isEnd:
 if state.winner == self.symbol:
 self.estimations[hash] = 1.0
 else:
 self.estimations[hash] = 0
 else:
 self.estimations[hash] = 0.5
 def feedState(self, state):
 self.states.append(state)
 def feedReward(self, reward):
 if len(self.states) == 0:
 return
```

```
self.states = [state.qetHash() for state in self.states]
 target = reward
 for latestState in reversed(self.states):
 value = self.estimations[latestState] + self.stepSize * (target - self.estim
 self.estimations[latestState] = value
 target = value
 self.states = []
def takeAction(self):
 state = self.states[-1]
 nextStates = []
 nextPositions = []
 for i in range(BOARD_ROWS):
 for j in range(BOARD_COLS):
 if state.data[i, j] == 0:
 nextPositions.append([i, j])
 nextStates.append(state.nextState(i, j, self.symbol).getHash())
 if np.random.binomial(1, self.exploreRate):
 np.random.shuffle(nextPositions)
 self.states = []
 action = nextPositions[0]
 action.append(self.symbol)
 return action
 values = [7]
 for hash, pos in zip(nextStates, nextPositions):
 values.append((self.estimations[hash], pos))
 np.random.shuffle(values)
 values.sort(key=lambda x: x[0], reverse=True)
 action = values[0][1]
 action.append(self.symbol)
 return action
def savePolicy(self):
 fw = open('optimal_policy_' + str(self.symbol), 'wb')
 pickle.dump(self.estimations, fw)
 fw.close()
def loadPolicy(self):
 fr = open('optimal_policy_' + str(self.symbol), 'rb')
 self.estimations = pickle.load(fr)
 fr.close()
```

```
| 1 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | 9 |
class HumanPlayer:
 def __init__(self, stepSize = 0.1, exploreRate=0.1):
 self.symbol = None
 self.currentState = None
 return
 def reset(self):
 return
 def setSymbol(self, symbol):
 self.symbol = symbol
 return
 def feedState(self, state):
 self.currentState = state
 return
 def feedReward(self, reward):
 return
 def takeAction(self):
 data = int(input("Input your position:"))
 data = 1
 i = data // int(BOARD_COLS)
 j = data % BOARD_COLS
 if self.currentState.data[i, j] != 0:
 return self.takeAction()
 return (i, j, self.symbol)
def train(epochs=20000):
 player1 = Player()
 player2 = Player()
 judger = Judger(player1, player2)
 player1Win = 0.0
 player2Win = 0.0
 for i in range(0, epochs):
 print("Epoch", i)
 winner = judger.play()
 if winner == 1:
 player1Win += 1
 if winner == -1:
 player2Win += 1
 judger.reset()
 print(player1Win / epochs)
 print(player2Win / epochs)
```

```
player1.savePolicy()
 player2.savePolicy()
def compete(turns=500):
 player1 = Player(exploreRate=0)
 player2 = Player(exploreRate=0)
 judger = Judger(player1, player2, False)
 player1.loadPolicy()
 player2.loadPolicy()
 player1Win = 0.0
 player2Win = 0.0
 for i in range(0, turns):
 print("Epoch", i)
 winner = judger.play()
 if winner == 1:
 player1Win += 1
 if winner == -1:
 player2Win += 1
 judger.reset()
 print(player1Win / turns)
 print(player2Win / turns)
def play():
 while True:
 player1 = Player(exploreRate=0)
 player2 = HumanPlayer()
 judger = Judger(player1, player2, False)
 player1.loadPolicy()
 winner = judger.play(True)
 if winner == player2.symbol:
 print("Win!")
 elif winner == player1.symbol:
 print("Lose!")
 else:
 print("Tie!")
train()
compete()
play()
11 11 11
```

 $\label{local_rows} $$ '\n\DOARD_ROWS = 3\nBOARD_COLS = 3\nBOARD_SIZE = BOARD_ROWS * BOARD_COLS\n\nclass State:\n $$ $$ $$$ 

### 4.1 k

k 1 k t  $A_t$   $R_t$  a  $X_a$  a

$$q_*(a) := \mathbb{E}[X_a]$$

t a  $Q_t(a)$   $q_*(a)$ 

## 4.2

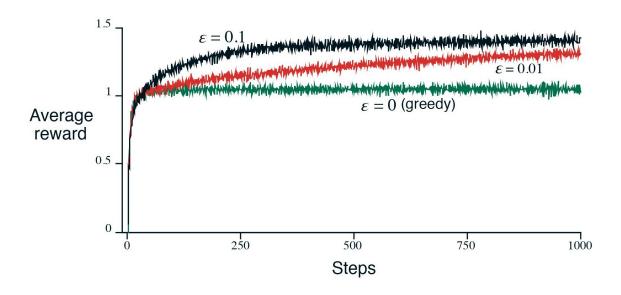
 $Q_t(a) := \frac{t \; a}{t \; a} = \frac{\sum_{i=1}^{t-1} R_i \; \mathbbm{1}_{A_i = a}}{\sum_{i=1}^{t-1} \mathbbm{1}_{A_i = a}}$ 

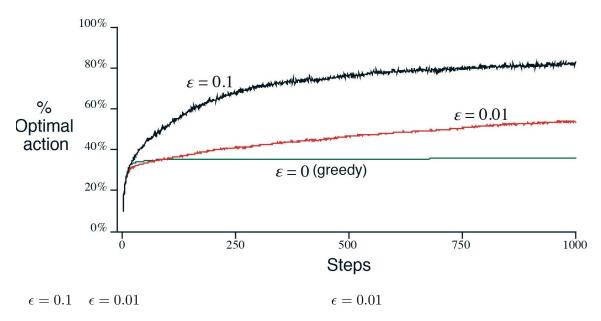
1 1 0

 $A_t = \arg \, \max_a Q_t(a)$ 

 $\operatorname{arg\ max}_a Q_t(a)$  a  $\epsilon$   $\epsilon$ 

### 4.3 10





$$1 \qquad \qquad n \qquad Q_n$$
 
$$Q_n := \frac{R_1 + R_2 + \cdots + R_n}{n-1}$$

 $R_n$   $Q_n$ 

$$Q_{n+1} = \frac{1}{n} \sum_{i=1}^n R_i = \frac{1}{n} (R_n + \sum_{i=1}^{n-1} R_i) = \frac{1}{n} (R_n + (n-1)Q_n) = Q_n + \frac{1}{n} (R_n - Q_n)$$
 
$$Q_n \ n$$

 $NewEstimate \leftarrow OldEstimate + StepSize \ [Target - OldEstimate]$ 

 $[Target-OldEstimate] \hspace{1cm} Target( \hspace{.1cm} n \hspace{.1cm} ) \hspace{1cm} StepSize \hspace{.1cm} 1/n \hspace{1cm} \alpha \hspace{.1cm} \alpha_t(a)$   $\epsilon$ - k

#### 4.5

 $Q_{n+1}$ 

( 
$$X_a)$$
 , 
$$\alpha \in (0,1]$$
 
$$Q_{n+1} := Q_n + \alpha [R_n - Q_n]$$

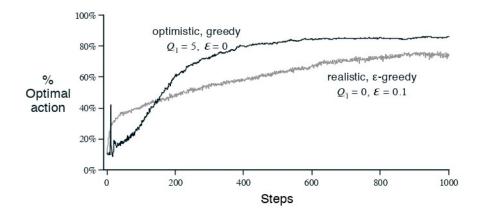
 $Q_{n+1} = Q_n + \alpha[R_n - Q_n] = \alpha R_n + (1 - \alpha)Q_n = \alpha R_n + (1 - \alpha)[\alpha R_{n-1} + (1 - \alpha)Q_{n-1}] = \alpha R_n + (1 - \alpha)\alpha R_{n-1} + (1 - \alpha)^2 Q_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1} + (1 - \alpha)Q_{n-1}) = \alpha R_n + (1 - \alpha)(\alpha R_{n-1}$ 

$$(1-a)^n + \sum_{i=1}^n \alpha (1-\alpha)^{n-i} = 1 \quad Q_{n+1} \qquad \qquad Q_1 \qquad \qquad 1-\alpha$$
 
$$\alpha \qquad \text{a n} \qquad \qquad \alpha_n(a) \qquad \qquad 1$$

$$\sum_{n=1}^{\infty}\alpha_n(a)=\infty \quad \sum_{n=1}^{\infty}\alpha_n^2(a)<\infty$$

```
print("Hello Python!")
```

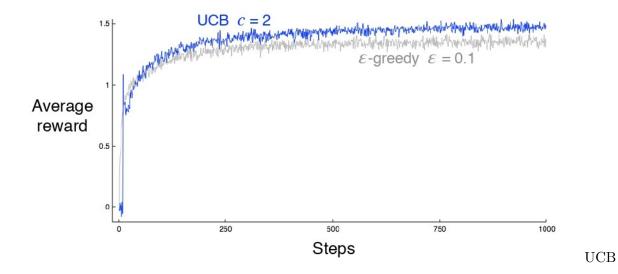
Hello Python!



4.7

 $\epsilon$ -

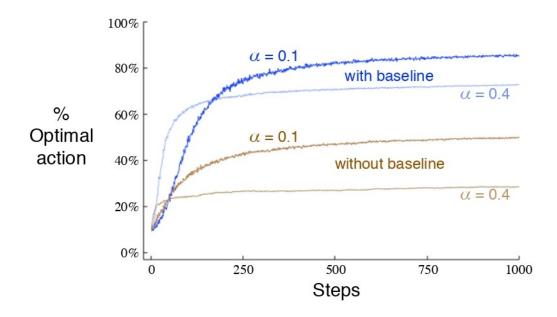
$$A_t := \arg \, \max_a \Biggl( Q_t(a) + c \sqrt{\frac{\log_e t}{N_t(a)}} \Biggr)$$
 
$$N_t(a) \ t \quad a \qquad c>0 \qquad \qquad \textbf{UCB} \quad \text{UCB} \quad 10$$



 $\epsilon$ -

$$a \qquad H_t(a)$$
 
$$\Pr\{A_t=a\}:=\pi_t(a):=\frac{e^{H_t(a)}}{\sum_{b=1}^k e^{H_t(b)}}$$
 
$$t \quad a \qquad \pi_t(a)$$
 
$$A_t \quad R_t$$

$$\begin{split} H_{t+1}(A_t) &= H_t(A_t) + \alpha (R_t - \overline{R}_t)(1 - \pi_t(A_t)), \\ H_{t+1}(a) &:= H_t(A_t) + \alpha (R_t - \overline{R}_t)\pi(a) \quad (a \neq A_t) \\ \overline{R}_t & \text{t} \\ &\text{k} \qquad q_*(a) \quad +4 \quad 1 \qquad \qquad \overline{R}_t = 0 \end{split}$$



k

