

Lecture H1. Value-based agent 1

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1 I. Algorithms overview

2 II. Deep Q-Learning

- `skier.R` is loaded as follows.

```
source("../skier.R")
```

```
## [1] "Skier's problem is set."
## [1] "Defined are `state`, `P_normal`, `P_speed`, `R_s_a`, `q_s_a_init` (F2, p15)."
```

```
## [1] "Defined are `pi_speed`, and `pi_50` (F2, p16)."
```

```
## [1] "Defined are `simul_path`() (F2, p17)."
```

```
## [1] "Defined are `simul_step`() (F2, p18)."
```

```
## [1] "Defined are `pol_eval_MC`() (F2, p19)."
```

```
## [1] "Defined are `pol_eval_TD`() (F2, p20)."
```

```
## [1] "Defined are `pol_imp`() (F2, p20)."
```

I. Algorithms overview

II. Deep Q-Learning

Motivation

- (pol_eval_MC()) MC control updates $q(s, a)$:

$$q(s, a) \leftarrow q(s, a) + \alpha(\underline{G_t} - q(s, a)), \quad \forall s, a$$

- (pol_eval_TD()) TD control updates $q(s, a)$:

$$q(s, a) \leftarrow q(s, a) + \alpha(\underline{r_t + \gamma q(s', a')} - q(s, a)), \quad \forall s, a$$

- (pol_eval_Q()) Q-learning updates $q(s, a)$:

$$q(s, a) \leftarrow q(s, a) + \alpha(\underline{r_t + \gamma \max_{a' \in \mathcal{A}} q(s', a')} - q(s, a)), \quad \forall s, a$$

- Deep Q-learning

- It approximates the $q(\cdot, \cdot)$ function with deep neural network.
- In other words, $q(\cdot, \cdot)$ approximates 'Q-target', $r_t + \gamma \max_{a' \in \mathcal{A}} q(s', a')$, using her experience.
- Improve her policy using the $q(\cdot, \cdot)$ network.



mc-tgt

TD-tgt

Q-tgt

Recap

● pol_eval_Q() (F4, p6) ✓

```
pol_eval_Q <- function(sample_step, q_s_a, alpha) {
  s <- sample_step[1]
  a <- sample_step[2]
  r <- sample_step[3] %>% as.numeric()
  s_next <- sample_step[4]
  q_s_a[s,a] <- q_s_a[s,a] + alpha*(r+max(q_s_a[s_next,])-q_s_a[s,a])
  return(q_s_a)
}
```

● pol_imp() (F2, p21) ✓

```
pol_imp <- function(pi, q_s_a, epsilon) { # epsilon = exploration_rate
  for (i in 1:nrow(pi)) {
    if (runif(1) > epsilon) { # exploitation
      pi[i, which.max(q_s_a[i,])] <- 1
      pi[i, -which.max(q_s_a[i,])] <- 0
    } else { # exploration
      pi[i,] <- 1/ncol(pi)
    }
  }
  return(pi)
}
```

Recap

● Q-learning (F4, p7)

```

num_ep <- 10^5
beg_time <- Sys.time()
q_s_a <- q_s_a_init #1. ✓
pi <- pi_50
exploration_rate <- 1
for (epi_i in 1:num_ep) {
  s_now <- "0"
  while (s_now != "70") {
    sample_step <- simul_step(
      pi, s_now, P_normal, P_speed, R_s_a)
    ✓ q_s_a <- pol_eval_Q(
      sample_step, q_s_a, alpha = max(1/epi_i, 0.05)) #2.
    if (epi_i %% 100 == 0) {
      pi <- pol_imp(pi, q_s_a, epsilon = exploration_rate) #3.
    }
    s_now <- sample_step[4]
    exploration_rate <- max(exploration_rate*0.9995, 0.001)
  }
}

```

● Strategy

- ① q_s_a needs to be defined as a DQN.
- ② pol_eval_DQN() needs to be written.
- ③ pol_imp_DQN() needs to be written.

0. Prep

- `vec2mat()` is to prepare input for `q_net`

```
vec2mat <- function(vec) {  
  return(matrix(vec, nrow=1, ncol=length(vec)))  
}  
a <- vec2mat(rep(0,8))  
class(a)
```

```
## [1] "matrix" "array"
```

```
dim(a)
```

```
## [1] 1 8
```

1. q_s_a needs to be defined as a DQN.

● Recap: q_s_a for $q(s, a)$

```
q_s_a_init <- cbind(rep(0,length(states)), rep(0,length(states)))
rownames(q_s_a_init) <- states
colnames(q_s_a_init) <- c("n", "s")
t(q_s_a_init)
```

```
##    0 10 20 30 40 50 60 70
## n  0  0  0  0  0  0  0  0
## s  0  0  0  0  0  0  0  0
```

● How to shape this into input-output structure?

```
library(data.table)
library(mltools)
action <- factor(c("n", "s"))
q_net_sketch <- data.frame(s = factor(states), a = factor(action)) %>%
  as.data.table()
q_net_sketch %>% one_hot() %>% colnames()

## [1] "s_0" "s_10" "s_20" "s_30" "s_40" "s_50" "s_60" "s_70" "a_n" "a_s"
```

● q_net() for q_s_a

```
library(keras)
q_net <- keras_model_sequential() %>%
  layer_dense(units = 16, input_shape = c(8), activation = "relu") %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(1, activation = "linear")
q_net %>% compile(loss = "mse", optimizer = "adam")
summary(q_net)
```

```
## Model: "sequential"
```

```
## _____
```

## Layer (type)	Output Shape	Param #
## =====		
## dense (Dense)	(None, 16)	144
## _____		
## dense_1 (Dense)	(None, 16)	272
## _____		
## dense_2 (Dense)	(None, 1)	17
## =====		
## Total params: 433		
## Trainable params: 433		
## Non-trainable params: 0		
## _____		

2. `pol_eval_DQN()` needs to be written.

● `pol_eval_Q()`

```
pol_eval_Q <- function(sample_step, q_s_a, alpha) {
  s <- sample_step[1]
  a <- sample_step[2]
  r <- sample_step[3] %>% as.numeric()
  s_next <- sample_step[4]
  q_s_a[s,a] <- q_s_a[s,a] +
    alpha*(r+max(q_s_a[s_next,])-q_s_a[s,a])
  return(q_s_a)
}
```

● `pol_eval_DQN()`

```
pol_eval_DQN <- function(sample_step, q_net) {
  s <- sample_step[1] %>% as.numeric()
  a <- sample_step[2]
  r <- sample_step[3] %>% as.numeric()
  s_next <- sample_step[4] %>% as.numeric()
  # Prepare `s_a_one_hot`
  s_a_one_hot <- c(rep(0,8))
  if (s < 70) s_a_one_hot[s/10+1] <- 1
  if (a=="n") s_a_one_hot[8] <- 1
  # Calculate `Q_tgt`
  s_next_one_hot <- c(rep(0,7))
  if (s_next < 70) {
    s_next_one_hot[s_next/10+1] <- 1
  }
  Q_tgt <- r + max(
    q_net %>% predict(vec2mat(c(s_next_one_hot,1)))
    q_net %>% predict(vec2mat(c(s_next_one_hot,0)))
  )
  # Update `q_net`
  q_net %>% fit(vec2mat(s_a_one_hot), Q_tgt,
    epoch=1, verbose = 0)
}
```

3. `pol_imp_DQN()` needs to be written.

● `pol_imp()`

```
pol_imp <- function(pi, q_s_a, epsilon) {
  for (i in 1:nrow(pi)) {
    if (runif(1) > epsilon) { # exploitation
      pi[i, which.max(q_s_a[i,])] <- 1
      pi[i, -which.max(q_s_a[i,])] <- 0
    } else { # exploration
      pi[i,] <- 1/ncol(pi)
    }
  }
  return(pi)
}
```

● `pol_imp_DQN()`

```
pol_imp_DQN <- function(pi, q_net, epsilon) {
  for (i in 1:nrow(pi)) {
    if (runif(1) > epsilon) { # exploitation
      s <- rownames(pi)[i] %>% as.numeric()
      s_one_hot <- c(rep(0,7))
      if (s < 70) s_one_hot[s/10+1] <- 1
      idx <- which.max(
        c(q_net %>% predict(
          vec2mat(c(s_one_hot, 1))),
          q_net %>% predict(
            vec2mat(c(s_one_hot, 0)))))
      pi[i, idx] <- 1
      pi[i, -idx] <- 0
    } else { # exploration
      pi[i,] <- 1/ncol(pi)
    }
  }
  return(pi)
}
```

Deep Q-Learnig

```

num_ep <- 500
q_net <- keras_model_sequential() %>% #1.
  layer_dense(16, input_shape = c(8),
              activation = "relu") %>%
  layer_dense(16, activation = "relu") %>%
  layer_dense(1, activation = "linear")
q_net %>%
  compile(loss = "mse", optimizer = "adam")
pi <- pi_50
explore_rate <- 1

```

```

for (epi_i in 1:num_ep) {
  s_now <- "0"
  while (s_now != "70") {
    sample_step <-
      simul_step(pi, s_now,
                 P_normal, P_speed, R_s_a)
    pol_eval_DQN(sample_step, q_net) #2.
    s_now <- sample_step[4]
  }
  q_net %>% fit(
    vec2mat(c(rep(0,7),1)),0, epoch=1, verbose=0)
  q_net %>% fit(
    vec2mat(c(rep(0,7),0)),0, epoch=1, verbose=0)
  if (epi_i %% 10 == 0) { #3.
    pi <- pol_imp_DQN(
      pi, q_net, epsilon = explore_rate)
  }
  explore_rate <- max(explore_rate*0.9995, 0.001)
}

```

Results

```
q_s_a_DQN <- pi
for (i in 1:nrow(q_s_a_DQN)) {
  s <- rownames(q_s_a_DQN)[i] %>% as.numeric()
  s_one_hot <- c(rep(0,7))
  if (s < 70) s_one_hot[s/10+1] <- 1
  q_s_a_DQN[i,1] <- q_net %>% predict(vec2mat(c(s_one_hot,1)))
  q_s_a_DQN[i,2] <- q_net %>% predict(vec2mat(c(s_one_hot,0)))
}
q_s_a_DQN
```

##	n	s
## 0	-5.79983	<u>-5.35285</u>
## 10	<u>-4.78158</u>	-4.92658
## 20	-3.90191	<u>-3.61255</u>
## 30	<u>-2.97708</u>	-3.50893
## 40	<u>-1.78193</u>	-1.90130
## 50	-1.86362	<u>-1.72882</u>
## 60	<u>-0.91133</u>	-1.78539
## 70	<u>0.04338</u>	<u>0.03107</u>

-1.67

"It's not that I'm so smart, it's just that I stay with problems longer. - A. Einstein"