

# 机器学习基础作业 6

2025 年 4 月 26 日

**问题 1.** 试用前向概率和后向概率推导

$$P(\mathbf{O}|\lambda) = \sum_{l=1}^N \sum_{k=1}^N \alpha_t(l) a_{lk} b_k(O_{t+1}) \beta_{t+1}(k)$$

证明.

$$P(\mathbf{O}|\lambda) = \sum_{l=1}^N \sum_{k=1}^N P(\mathbf{O}, X_t = s_l, X_{t+1} = s_k | \lambda)$$

注意到:

$$\begin{aligned} \alpha_t(l) a_{lk} &= P(O_1, O_2, \dots, O_t, X_t = s_l | \lambda) P(X_{t+1} = s_k | X_t = s_l, \lambda) \\ &= P(O_1, O_2, \dots, O_t, X_t = s_l, X_{t+1} = s_k | \lambda) \end{aligned}$$

$$\begin{aligned} b_k(O_{t+1}) \beta_{t+1}(k) &= P(O_{t+1} | X_{t+1} = s_k, \lambda) P(O_{t+2}, O_{t+3}, \dots, O_T | X_{t+1} = s_k, \lambda) \\ &= P(O_{t+1}, O_{t+2}, \dots, O_T | X_{t+1} = s_k, \lambda) \\ &= P(O_{t+1}, O_{t+2}, \dots, O_T | X_t = s_l, X_{t+1} = s_k, \lambda) \end{aligned}$$

最后这一行是因为马尔可夫性质,  $X_{t+1}$  已知时,  $O_{t+1}$  与  $X_t$  无关. 因而二者相乘即有:

$$\begin{aligned} P(\mathbf{O}|\lambda) &= \sum_{l=1}^N \sum_{k=1}^N P(O_1, O_2, \dots, O_t, X_t = s_l, X_{t+1} = s_k, O_{t+1}, O_{t+2}, \dots, O_T | \lambda) \\ &= \sum_{l=1}^N \sum_{k=1}^N P(O_1, O_2, \dots, O_t, X_t = s_l, X_{t+1} = s_k | \lambda) P(O_{t+1}, O_{t+2}, \dots, O_T | X_t = s_l, X_{t+1} = s_k, \lambda) \\ &= \sum_{l=1}^N \sum_{k=1}^N \alpha_t(l) a_{lk} b_k(O_{t+1}) \beta_{t+1}(k) \end{aligned}$$

□

**问题 2.** 证明维特比算法中  $\delta$  的递推公式.

证明.

$$\begin{aligned} \delta_t(i) &= \max_{X_1, X_2, \dots, X_{t-1}} P(X_1, X_2, \dots, X_{t-1}, O_1, O_2, \dots, O_t, X_t = s_i | \lambda) \\ &= \max_{X_1, X_2, \dots, X_{t-2}} \max_{1 \leq j \leq N} P(X_1, X_2, \dots, X_{t-1} = s_j, O_1, O_2, \dots, O_t, X_t = s_i | \lambda) \\ &= \max_{1 \leq j \leq N} \max_{X_1, X_2, \dots, X_{t-2}} P(X_1, X_2, \dots, X_{t-2}, O_1, O_2, \dots, O_{t-1}, X_{t-1} = s_j, X_t = s_i | \lambda) P(O_t | X_t = s_i) \\ &= \max_{1 \leq j \leq N} \max_{X_1, X_2, \dots, X_{t-2}} P(X_1, X_2, \dots, X_{t-2}, O_1, O_2, \dots, O_{t-1}, X_{t-1} = s_j | \lambda) P(X_t = s_i | X_{t-1} = s_j) b_i(O_t) \\ &= \max_{1 \leq j \leq N} \delta_{t-1}(j) b_i(O_t) a_{ji} = \max_{1 \leq j \leq N} (\delta_{t-1}(j) a_{ji}) b_i(O_t) \end{aligned}$$

其中第三行用到了马尔可夫性质, 当  $X_t$  已知时观测结果  $O_t$  与  $X_1, \dots, X_{t-1}$  无关.

□

**问题 3.** 在下述隐马尔可夫模型  $\lambda = (A, B, \pi)$  中, 可能的观测值集合为  $\{\nu_1, \nu_2, \nu_3\}$ , 可能的状态集为  $\{q_1, q_2, q_3\}$ ,  $A = \begin{bmatrix} 0.6 & 0.2 & 0.2 \\ 0.3 & 0.5 & 0.2 \\ 0.3 & 0.3 & 0.4 \end{bmatrix}$ ,  $B = \begin{bmatrix} 0.2 & 0.5 & 0.3 \\ 0.6 & 0.2 & 0.2 \\ 0.3 & 0.3 & 0.4 \end{bmatrix}$ ,  $\pi = (0.6, 0.2, 0.2)^T$ , 观察序列  $O = (\nu_3, \nu_2, \nu_1)$ , 用维特比算法求最优状态序列.

证明. 初值:

$$\delta_1(1) = \pi_1 b_1(O_1) = 0.6 \cdot 0.3 = 0.18$$

$$\delta_1(2) = \pi_2 b_2(O_1) = 0.2 \cdot 0.2 = 0.04$$

$$\delta_1(3) = \pi_3 b_3(O_1) = 0.2 \cdot 0.4 = 0.08$$

第二项:

$$\delta_2(1) = \max_{1 \leq j \leq 3} (\delta_1(j) a_{j1}) b_1(O_2) = \max(0.18 \cdot 0.6, 0.04 \cdot 0.3, 0.08 \cdot 0.3) \cdot 0.5 = 0.054$$

$$\delta_2(2) = \max_{1 \leq j \leq 3} (\delta_1(j) a_{j2}) b_2(O_2) = \max(0.18 \cdot 0.2, 0.04 \cdot 0.5, 0.08 \cdot 0.3) \cdot 0.2 = 0.0072$$

$$\delta_2(3) = \max_{1 \leq j \leq 3} (\delta_1(j) a_{j3}) b_3(O_2) = \max(0.18 \cdot 0.2, 0.04 \cdot 0.2, 0.08 \cdot 0.4) \cdot 0.3 = 0.0108$$

且最优历史为  $\Psi_2(1) = 1, \Psi_2(2) = 1, \Psi_2(3) = 1$ . 第三项:

$$\delta_3(1) = \max_{1 \leq j \leq 3} (\delta_2(j) a_{j1}) b_1(O_3) = \max(0.054 \cdot 0.6, 0.0072 \cdot 0.3, 0.0108 \cdot 0.3) \cdot 0.2 = 0.00648$$

$$\delta_3(2) = \max_{1 \leq j \leq 3} (\delta_2(j) a_{j2}) b_2(O_3) = \max(0.054 \cdot 0.2, 0.0072 \cdot 0.5, 0.0108 \cdot 0.3) \cdot 0.6 = 0.00648$$

$$\delta_3(3) = \max_{1 \leq j \leq 3} (\delta_2(j) a_{j3}) b_3(O_3) = \max(0.054 \cdot 0.2, 0.0072 \cdot 0.2, 0.0108 \cdot 0.4) \cdot 0.3 = 0.00324$$

且最优历史为  $\Psi_3(1) = 1, \Psi_3(2) = 1, \Psi_3(3) = 1$ . 注意  $\delta_3(1)$  和  $\delta_3(2)$  同为最大值, 因此最优路径有两条:  $(q_1, q_1, q_1)$  和  $(q_1, q_1, q_2)$ .

□