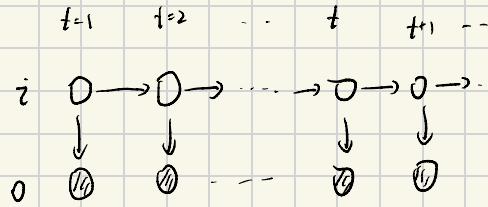


HMM 隐马尔可夫模型

频率派 → 统计机器学习

贝叶斯派 → 概率图模型



$I = (i_1, i_2, \dots, i_T)$ — 状态序列

$O = (O_1, O_2, \dots, O_T)$ — 观测序列

$Q = \{q_1, q_2, \dots, q_N\}$ — 状态集合
 $V = \{v_1, v_2, \dots, v_m\}$ — 观测集合

隐马尔可夫模型

$$\lambda = (\pi, A, B)$$

$\pi = (\pi_i) = (P(i_1 = q_i)), i=1, 2, \dots, N$ - 初始状态向量

$A = [a_{ij}]_{N \times N} \quad a_{ij} = P(i_{t+1} = q_j | i_t = q_i)$ — 状态转移矩阵

$B = [b_j(k)]_{N \times m} \quad b_j(k) = P(O_t = v_k | i_t = q_j)$ — 双向概率矩阵

①齐次马尔可夫假设

$$P(i_{t+1}|i_t, O_1, i_1, O_1, \dots) = P(i_{t+1}|i_t)$$

②观测独立假设

$$P(O_t|i_t, i_{t+1}, \dots, i_1, O_{t+1}, \dots, O_T) = P(O_t|i_t)$$

三个问题

① Evaluation (given λ , find $P(I|\lambda)$) → 前向后向算法

② learning $\lambda_{MLE} = \arg \max_{\lambda} P(I|\lambda)$ → EM

③ decoding

$$\hat{I} = \arg \max_I P(I|O, \lambda)$$

HMM Evaluation: 求 $p(O; \lambda)$

$$\therefore p(O; \lambda) = \sum_I p(O|I; \lambda) \cdot p(I; \lambda)$$

1. 直接计算法

$$p(O; \lambda) = \sum_I p(O|I; \lambda) \cdot p(I; \lambda)$$

$$= \sum_{i_1, i_2, \dots, i_t} \pi_{i_1} a_{i_1} a_{i_2} \dots a_{i_t} b_{i_1} b_{i_2} \dots b_{i_t} l_{i_1} l_{i_2} \dots l_{i_t}$$

$$p(I; \lambda) = p(i_1, i_2, i_3, \dots, i_{t-1}, i_t)$$

上面的公式要对所有状态求和，每个状态有n个状态。

$$= p(\bar{i}_t | i_1, i_2, i_3, \dots, i_{t-1}) \cdot p(i_1, i_2, i_3, \dots, i_{t-1})$$

马尔可夫假设

复杂度 $O(TN^T)$ 指数阶不可行

$$= a_{i_{t+1} i_t} \cdot p(i_1, i_2, i_3, \dots, i_{t-1})$$

递归化简

$$= a_{i_t i_t} \cdot a_{i_{t-1} i_t} \dots a_{i_1 i_2} \cdot \pi_{i_1}$$

$$p(O|I; \lambda) = p(O_1, O_2, \dots, O_{t-1} | i_1, i_2, \dots, i_t; \lambda)$$

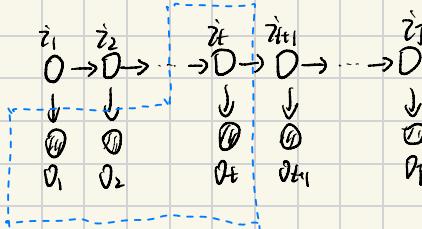
$$= p(O_t | O_1, O_2, \dots, O_{t-1}, i_1, i_2, \dots, i_t; \lambda)$$

观测独立假设 $p(O_t | i_t; \lambda)$

$$\cdot p(O_1, O_2, \dots, O_{t-1} | i_1, i_2, \dots, i_t; \lambda)$$

$$= b_{i_t}(O_t) \cdot b_{i_{t-1}}(O_{t-1}) \dots b_{i_1}(O_1)$$

2. 前向算法



$$\alpha_t(i) = P(o_1, o_2, \dots, o_t, z_t = q_i; \lambda)$$

$$d_T(i) = P(o, z_T = q_i; \lambda)$$

$$P(o, \lambda) = \sum_{i=1}^N P(o, z_T = q_i; \lambda) \quad \text{对 } z_T \text{ 的 } N \text{ 个状态求和}$$

$$= \sum_{i=1}^N d_T(i)$$

下面就探寻 $d_T(i)$ 是否可以从前向概率 $\alpha_{t+1}(j)$ 直推得到

$$\alpha_{t+1}(j) = P(o_1, o_2, \dots, o_t, o_{t+1}, z_{t+1} = q_j; \lambda)$$

$$= \sum_{i=1}^N P(o_1, o_2, \dots, o_t, o_{t+1}, z_{t+1} = q_j, z_t = q_i; \lambda)$$

$$= \sum_{i=1}^N P(o_{t+1} | o_1, \dots, o_t, z_{t+1} = q_j, z_t = q_i; \lambda) \cdot P(o_1, \dots, o_t, z_{t+1} = q_j, z_t = q_i; \lambda)$$

独立观测假设

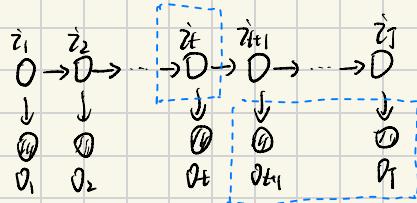
$$= \sum_{i=1}^N \underbrace{P(o_{t+1} | z_{t+1} = q_j)}_{b_j(o_{t+1})} \cdot \underbrace{P(z_{t+1} = q_j | o_1, \dots, o_t, z_t = q_i; \lambda)}_{a_{ij}} \cdot P(o_1, \dots, o_t, z_t = q_i; \lambda)$$

$$\cdot P(o_1, \dots, o_t, z_t = q_i; \lambda)$$

$$\underbrace{d_T(i)}$$

$$= \sum_{i=1}^N d_T(i) a_{ij} \cdot b_j(o_{t+1})$$

3. 后向算法



$$\text{记 } \beta_t(z_i) = P(O_{t+1}, O_{t+2}, \dots, O_T | z_t = q_i; \lambda)$$

$$\Rightarrow \beta_t(z_i) = P(O_2, \dots, O_T | z_1 = q_i; \lambda)$$

$$P(O; \lambda) = P(O_1, O_2, \dots, O_T; \lambda)$$

$$= \sum_{j=1}^N P(O_1, O_2, \dots, O_T, z_j = q_i; \lambda)$$

$$= \sum_{j=1}^N P(O_1, O_2, \dots, O_T | z_i = q_i; \lambda) \underbrace{P(z_i = q_i)}_{\pi_i}$$

$$= \sum_{j=1}^N P(O_1, O_2, \dots, O_T, z_i = q_i; \lambda) \cdot \underbrace{P(O_2, \dots, O_T | z_i = q_i; \lambda)}_{\beta_t(z_i)} \cdot \pi_i$$

$$= \sum_{j=1}^N \underbrace{P(O_1 | z_i = q_i; \lambda)}_{B_i(O_1)} \cdot \underbrace{\beta_t(z_i)}_{\beta_t(z_i)} \cdot \pi_i$$

$$= \sum_{j=1}^N B_i(O_1) \cdot \beta_t(z_i) \cdot \pi_i$$

$$\beta_t(z_i) = P(O_{t+1}, \dots, O_T | z_t = q_i)$$

$$= \sum_{j=1}^N P(O_{t+1}, \dots, O_T, z_{t+1} = q_j | z_t = q_i)$$

$$= \sum_{j=1}^N P(O_{t+1}, \dots, O_T | z_{t+1} = q_j, z_t = q_i) \cdot P(z_{t+1} = q_j | z_t = q_i)$$

| 概率因性质

$$= \sum_{j=1}^N P(O_{t+1}, \dots, O_T | z_{t+1} = q_j) \cdot a_{ij}$$

$$= \sum_{j=1}^N P(O_{t+1} | O_{t+2}, \dots, O_T, z_{t+1} = q_j) \cdot P(O_{t+2}, \dots, O_T | z_{t+1} = q_j) \cdot a_{ij}$$

$$= \sum_{j=1}^N P(O_{t+1} | z_{t+1} = q_j) \cdot \beta_{t+1}(j) \cdot a_{ij}$$

$$= \sum_{j=1}^N b_j(O_{t+1}) \cdot \beta_{t+1}(j) \cdot a_{ij}$$

利用前向后向概率可以将观测序列写成：

$$P(O|\lambda) = \sum_{i=1}^N \sum_{j=1}^N a_{ij} b_j(O_1) \beta_{t+1}(j), t=1, 2, \dots, T-1$$