

第三次作业（贝叶斯网络）

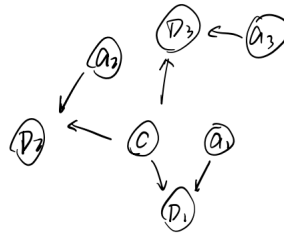
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问题 1：概率推断

a.

1. (a).



b.

$$\begin{aligned}
 (b). \quad & P(C=c, D_1=d_1, D_2=d_2, D_3=d_3) \\
 &= p(c) p(d_1|c, a_1) p(d_2|c, a_2) p(d_3|c, a_3)
 \end{aligned}$$

c.

$$\begin{aligned}
 (c). \quad LHS &= \frac{P(C=c, D_1=d_1, \dots, D_t=d_t)}{P(D_1=d_1, \dots, D_t=d_t)} \\
 &= \frac{p(c)p(d_1|c) \dots p(d_t|c)}{p(d_1|d_1, \dots, d_{t-1}) \cdot p(d_t|d_1, \dots, d_{t-1})} \\
 RHS &= \frac{p(c)p(d_1|c) \dots p(d_t|c)}{P(D_1=d_1, \dots, D_{t-1}=d_{t-1})} \cdot p(d_t|c) \\
 &= \frac{LHS}{p(d_t|d_1, \dots, d_{t-1})} \quad d_1 \text{ 至 } d_{t-1} \text{ 已知} \quad \text{则} \quad LHS = RHS \quad \text{Conse.}
 \end{aligned}$$

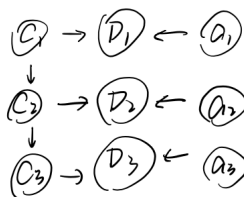
d.

```
def observe(self, agentX: int, agentY: int, observedDist: float) -> None:
    # BEGIN_YOUR_CODE (our solution is 7 lines of code, but don't worry if you
    # deviate from this)
    for row in range(self.belief.numRows):
        for col in range(self.belief.numCols):
            prob = self.belief.getProb(row, col)    # Probability at current index
            targetX, targetY = util.colToX(col), util.rowToY(row)    # Get location
            # of current index
            distance = math.sqrt(math.pow(agentX-targetX, 2)+math.pow(agentY-targetY
            , 2))
            multiplier = util.pdf(distance, Const.SONAR_STD, observedDist)
            self.belief.setProb(row, col, prob*multiplier)
        self.belief.normalize()
    # END_YOUR_CODE
```

问题 2：转移概率

a.

2- (a).



b.

$$\begin{aligned}
 (b). \quad & P(C_1=c_1, C_2=c_2, C_3=c_3, D_1=d_1, D_2=d_2, D_3=d_3) \\
 &= p(c_1)p(c_2|c_1)p(c_3|c_2)p(d_1|c_1,a_1)p(d_2|c_2,a_2)p(d_3|c_3,a_3)
 \end{aligned}$$

c.

$$\begin{aligned}
 (c), LHS &= \sum_{C_t} P(C_{t+1}, C_t | d_1, \dots, d_t) \\
 P(C_{t+1}, C_t | d_1, \dots, d_t) &= \frac{P(C_{t+1}, C_t, d_1, \dots, d_t)}{P(d_1, \dots, d_t)} \\
 &= \frac{P(C_{t+1} | C_t, d_1, \dots, d_t) P(C_t, d_1, \dots, d_t)}{P(d_1, \dots, d_t)} \\
 &\quad // \\
 &\quad P(C_{t+1} | C_t) \\
 &= P(C_t | d_1, \dots, d_t) P(C_{t+1} | C_t) \\
 LHS &= \sum_{C_t} P(C_t | d_1, \dots, d_t) P(C_{t+1} | C_t)
 \end{aligned}$$

d.

```

def elapseTime(self) -> None:
    if self.skipElapse: ### ONLY FOR THE GRADER TO USE IN Problem 1
        return
    # BEGIN_YOUR_CODE (our solution is 7 lines of code, but don't worry if you
    # deviate from this)
    temp_belief = self.belief
    for row in range(self.belief.numRows):
        for col in range(self.belief.numCols):
            prob = 0.0
            for key in self.transProb:
                if key[1] == (row, col):
                    prob += self.belief.getProb(key[0][0], key[0][1]) * self.transProb[key]
            temp_belief.setProb(row, col, prob)
    temp_belief.normalize()
    self.belief = temp_belief
    # END_YOUR_CODE

```

问题 3: 是哪辆车?

a.

3. (a).

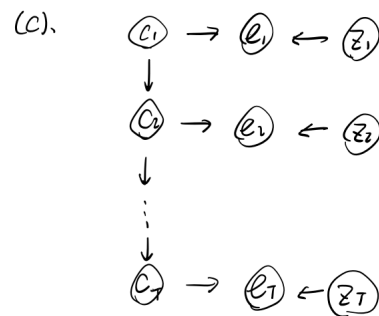
$$\begin{aligned}
 p(c_{n1}, c_{n2} | e_1) &= \frac{p(c_{n1}, c_{n2}, e_1)}{p(e_1)} = \frac{p(e_1 | c_{n1}, c_{n2}) \overbrace{p(c_{n1}, c_{n2})}^{=p(c_{n1})p(c_{n2})}}{p(e_1)} \\
 p(e_1 | c_{n1}, c_{n2}) &= 0.5 \cdot p_N(e_1; \|a_1 - c_{n1}\|_2, \sigma^2) \\
 &\quad + 0.5 \cdot p_N(e_1; \|a_1 - c_{n2}\|_2, \sigma^2) \\
 \text{则 } p(c_{n1}, c_{n2} | e_1) &\propto \\
 &\quad [p_N(e_1; \|a_1 - c_{n1}\|_2, \sigma^2) + p_N(e_1; \|a_1 - c_{n2}\|_2, \sigma^2)] \cdot p(c_{n1}) p(c_{n2})
 \end{aligned}$$

b.

(b). 设 z_t 为 t 时间步索引向右移动的数目, 取值为 $0, 1, \dots, K-1$
 对每一个 z_t , 取 $[0, K-1]$ 上各整数值概率均等, i.e. $\frac{1}{K}$

$$\begin{aligned}
 p(c_t | c_{t-1}) &= \sum_{z_t} p(c_t | c_{t-1}, z_t) p(z_t) \\
 &= \frac{1}{K} \sum_{z_t} p(c_t | c_{t-1}, z_t)
 \end{aligned}$$

c.



$$\begin{aligned}
 p(c_t, e_1, \dots, e_T) &= p(c_t | c_{t-1}) p(e_1 | c_1, z_1) \dots p(e_T | c_T, z_T) \\
 &= p(c_t | c_{t-1}) \\
 &= p(c_t | e_1, \dots, e_T) p(e_1, \dots, e_T) \\
 p(e_1, \dots, e_T) &= p(e_1 | c_1, z_1) \dots p(e_T | c_T, z_T) \\
 p(c_t | e_1, \dots, e_T) &= \frac{1}{K} \sum_{z_t} p(c_t | c_{t-1}, z_t)
 \end{aligned}$$

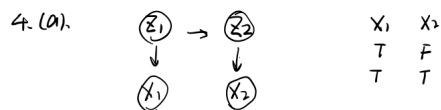
d.

粒子滤波相比精确推理，速度上有明显的提升，另外成功率也有显著改善，在车辆数增加的情况下也是如此。

原因是精确推理需要存储整个空间上的概率分布，导致计算的复杂度很高。而粒子滤波使用一组有限数量的粒子，计算复杂度主要取决于粒子的数量而非状态空间。

问题 4：模型学习

a.



E步: 第一个分量:

$$P(Z_1 | X_1) = \frac{P(X_1 | Z_1) P(Z_1)}{P(X_1)}$$

$$P(Z_1 = \text{true} | X_1 = \text{true}) = \frac{0.9 \cdot 0.6}{1} = 0.54$$

$$P(Z_1 = \text{false} | X_1 = \text{true}) = 0.46$$

$$P(Z_2 | X_2) = \frac{P(X_2 | Z_2) P(Z_2 | Z_1)}{P(X_2)}$$

$$P(Z_2 = \text{true} | X_2 = \text{false})$$

$$= 0.7 \cdot (0.54 \times 0.7 + 0.46 \times 0.2) = 0.329$$

$$P(Z_2 = \text{false} | X_2 = \text{false}) = 0.671$$

第二个分量 (即 X_2 改为 true)

$$P(Z_2 = \text{true} | X_2 = \text{true})$$

$$= 0.3 \cdot (0.57 \times 0.7 + 0.46 \times 0.2) = 0.141$$

$$P(Z_2 = \text{false} | X_2 = \text{true}) = 0.859$$

反馈

- 代码部分没有难度，书写部分 3, 4 题感觉有些难度，无论是在理解题意上还是在解题上。
- 整体用时在 20h 左右，大部分是在做计算以及证明题。