

# CS221 Problem Workout

Week 8

## 1) [CA session] Problem 1: The Bayesian Bag of Candies Model

You have a lot of candy left over from Halloween, and you decide to give them away to your friends. You have four types of candy: **A**pple, **B**anana, **C**aramel, **D**ark-Chocolate. You decide to prepare candy bags using the following process.

- For each candy bag, you first flip a (biased) coin  $Y$  which comes up heads ( $Y = H$ ) with probability  $\lambda$  and tails ( $Y = T$ ) with probability  $1 - \lambda$ .
- If  $Y$  comes up heads ( $Y = H$ ), you make a **H**ealthy bag, where you:
  - (a) Add one **A**pple candy with probability  $p_1$  or nothing with probability  $1 - p_1$ ;
  - (b) Add one **B**anana candy with probability  $p_1$  or nothing with probability  $1 - p_1$ ;
  - (c) Add one **C**aramel candy with probability  $1 - p_1$  or nothing with probability  $p_1$ ;
  - (d) Add one **D**ark-Chocolate candy with probability  $1 - p_1$  or nothing with probability  $p_1$ .
- If  $Y$  comes up tails ( $Y = T$ ), you make a **T**asty bag, where you:
  - (a) Add one **A**pple candy with probability  $p_2$  or nothing with probability  $1 - p_2$ ;
  - (b) Add one **B**anana candy with probability  $p_2$  or nothing with probability  $1 - p_2$ ;
  - (c) Add one **C**aramel candy with probability  $1 - p_2$  or nothing with probability  $p_2$ ;
  - (d) Add one **D**ark-Chocolate candy with probability  $1 - p_2$  or nothing with probability  $p_2$ .

For example, if  $p_1 = 1$  and  $p_2 = 0$ , you would deterministically generate: **H**ealthy bags with one **A**pple and one **B**anana; and **T**asty bags with one **C**aramel and one **D**ark-Chocolate. For general values of  $p_1$  and  $p_2$ , bags can contain anywhere between 0 and 4 pieces of candy.

Denote  $A, B, C, D$  random variables indicating whether or not the bag contains candy of type **A**pple, **B**anana, **C**aramel, and **D**ark-Chocolate, respectively.

**a.** (1 point)

(i) Draw the Bayesian network corresponding to process of creating a single bag.

(ii) What is the probability of generating a **Healthy** bag containing **Apple**, **Banana**, **Caramel**, and not **Dark-Chocolate**? For compactness, we will use the following notation to denote this possible outcome:

(**Healthy**, {**Apple**, **Banana**, **Caramel**}).

(iii) What is the probability of generating a bag containing **Apple**, **Banana**, **Caramel**, and *not* **Dark-Chocolate**?

(iv) What is the probability that a bag was a **Tasty** one, given that it contains **Apple**, **Banana**, **Caramel**, and *not* **Dark-Chocolate**?

**b.** (1 point)

You realize you need to make more candy bags, but you've forgotten the probabilities you used to generate them. So you try to estimate them looking at the 5 bags you've already made:

<i>bag</i> 1 :	( <b>H</b> ealthy, { <b>A</b> pple, <b>B</b> anana})
<i>bag</i> 2 :	( <b>T</b> asty, { <b>C</b> aramel, <b>D</b> ark-Chocolate})
<i>bag</i> 3 :	( <b>H</b> ealthy, { <b>A</b> pple, <b>B</b> anana})
<i>bag</i> 4 :	( <b>T</b> asty, { <b>C</b> aramel, <b>D</b> ark-Chocolate})
<i>bag</i> 5 :	( <b>H</b> ealthy, { <b>A</b> pple, <b>B</b> anana})

Estimate  $\lambda, p_1, p_2$  by maximum likelihood.

Estimate  $\lambda, p_1, p_2$  by maximum likelihood, using Laplace smoothing with parameter 1.

**c.** (1 point) You find out your little brother had been playing with your candy bags, and had mixed them up (in a uniformly random way). Now you don't even know which ones were **H**ealthy and which ones were **T**asty. So you need to re-estimate  $\lambda, p_1, p_2$ , but now without knowing whether the bags were **H**ealthy or **T**asty.

*bag* 1 :                    (? , {**A**pple, **B**anana, **C**aramel})  
*bag* 2 :                    (? , {**C**aramel, **D**ark-Chocolate})  
*bag* 3 :                    (? , {**A**pple, **B**anana, **C**aramel})  
*bag* 4 :                    (? , {**C**aramel, **D**ark-Chocolate})  
*bag* 5 :                    (? , {**A**pple, **B**anana, **C**aramel})

You remember the EM algorithm is just what you need. Initialize with  $\lambda = 0.5, p_1 = 0.5, p_2 = 0$ , and run one step of the EM algorithm.

(i) E-step:

(ii) M-step:

d. (1 point)

You decide to make candy bags according to a new process. You create the first one as described above. Then with probability  $\mu$ , you create a second bag of the same type as the first one (Healthy or Tasty), and of different type with probability  $1 - \mu$ . Given this type, the bag is filled with candy as before. Then with probability  $\mu$ , you create a third bag of the same type as the second one (Healthy or Tasty), and of different type with probability  $1 - \mu$ . And so on, you repeat the process  $M$  times. Denote  $Y_i, A_i, B_i, C_i, D_i$  the variables at each time step, for  $i = 0, \dots, M$ . Let  $X_i = (A_i, B_i, C_i, D_i)$ .

Now you want to compute:

$$\mathbb{P}(Y_i = \mathbf{Healthy} \mid X_0 = (1, 1, 1, 0), \dots, X_i = (1, 1, 1, 0))$$

exactly for all  $i = 0, \dots, M$ , and you decide to use the forward-backward algorithm.

Suppose you have already computed the marginals:

$$f_i = \mathbb{P}(Y_i = \mathbf{Healthy} \mid X_0 = (1, 1, 1, 0), \dots, X_i = (1, 1, 1, 0))$$

for some  $i \geq 0$ . Recall the first step of the algorithm is to compute an intermediate result *proportional* to

$$\mathbb{P}(Y_{i+1} \mid X_0 = (1, 1, 1, 0), \dots, X_i = (1, 1, 1, 0), X_{i+1} = (1, 1, 1, 0))$$

(i) Write an expression that is **proportional** to

$$\mathbb{P}(Y_{i+1} = \mathbf{Healthy} \mid X_0 = (1, 1, 1, 0), \dots, X_i = (1, 1, 1, 0), X_{i+1} = (1, 1, 1, 0))$$

in terms of  $f_i$  and the parameters  $p_1, p_2, \lambda, \mu$ .

(ii) Write an expression that is **proportional** to

$$\mathbb{P}(Y_{i+1} = \mathbf{Tasty} \mid X_0 = (1, 1, 1, 0), \dots, X_i = (1, 1, 1, 0), X_{i+1} = (1, 1, 1, 0))$$

in terms of  $f_i$  and the parameters of the model  $p_1, p_2, \lambda, \mu$ . The proportionality constant should be the same as in (i).

(iii) Let  $h$  be the answer for part (i), and  $t$  for part (ii). Write an expression for

$$\mathbb{P}(Y_{i+1} = \mathbf{Healthy} \mid X_0 = (1, 1, 1, 0), \dots, X_i = (1, 1, 1, 0), X_{i+1} = (1, 1, 1, 0))$$

in terms of  $h, t$  and the parameters of the model  $p_1, p_2, \lambda, \mu$ .