

# CS 361 Spring 2018

## Homework 8

Nathaniel Murphy (njmurph3)

### 9.1

(a)

Show that MLE of a dataset following the normal distribution is  $\text{mean}(\{x\})$ .

$$\begin{aligned}\mathcal{L}(\Theta) &= P(x_1, \dots, x_N \mid \Theta, \sigma) \\&= P(x_1 \mid \Theta, \sigma) P(x_2 \mid \Theta, \sigma) \dots P(x_N \mid \Theta, \sigma) \\&= \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x_i - \Theta)^2}{2\sigma^2}} \\ \log \mathcal{L}(\Theta) &= \sum_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma} + \sum_{i=1}^N -\frac{(x_i - \Theta)^2}{2\sigma^2} \\&= \frac{N}{\sqrt{2\pi}\sigma} - \frac{1}{\sigma^2} \sum_{i=1}^N (x_i - \Theta)^2 \\ \frac{\partial}{\partial \Theta} \log \mathcal{L}(\Theta) &= 0 - \frac{1}{\sigma^2} \sum_{i=1}^N (x_i - \Theta)\end{aligned}$$

Set the derivative equal to zero.

$$\begin{aligned}0 &= \frac{1}{\sigma^2} \sum_{i=1}^N (x_i - \Theta) \\ 0 &= \sum_{i=1}^N (x_i) - N\Theta \\ \Theta &= \frac{\sum_{i=1}^N x_i}{N} = \text{mean}(\{x\})\end{aligned}$$

(b)

Show that the MLE for the standard deviation is  $\text{std}(\{x\})$ .

$$\begin{aligned}\mathcal{L}(\Theta) &= P(x_1, \dots, x_N \mid \Theta, \sigma) \\ &= P(x_1 \mid \Theta, \mu) P(x_2 \mid \Theta, \mu) \dots P(x_N \mid \Theta, \mu) \\ &= \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\Theta} e^{-\frac{(x_i - \mu)^2}{2\Theta^2}} \\ \log \mathcal{L}(\Theta) &= \sum_{i=1}^N \log \left( \frac{1}{\sqrt{2\pi}\Theta} \right) + \sum_{i=1}^N -\frac{(x_i - \mu)^2}{2\Theta^2} \\ &= N \log(1) - N \log(\sqrt{2\pi}) - N \log(\Theta) - \frac{1}{\Theta^2} \sum_{i=1}^N \frac{(x_i - \mu)^2}{2} \\ \frac{\partial}{\partial \Theta} \log \mathcal{L}(\Theta) &= -\frac{N}{\Theta} + \frac{2}{\Theta^3} \sum_{i=1}^N \frac{(x_i - \mu)^2}{2}\end{aligned}$$

Set derivative equal to zero.

$$\begin{aligned}0 &= -\frac{N}{\Theta} + \frac{2}{\Theta^3} \sum_{i=1}^N \frac{(x_i - \mu)^2}{2} \\ \frac{N}{\Theta} &= \frac{2}{\Theta^3} \sum_{i=1}^N \frac{(x_i - \mu)^2}{2} \\ \Theta^2 &= \frac{2}{N} \sum_{i=1}^N \frac{(x_i - \mu)^2}{2} \\ \Theta &= \sqrt{\frac{\sum_{i=1}^N (x_i - \mu)^2}{N}} = \text{std}(\{x\})\end{aligned}$$

(c)

If all numbers  $x_1, \dots, x_N$  take the same value, we have  $\text{mean}(\{x\}) = x_i \forall i \in [1, N]$ .

$$\text{std}(\{x\}) = \sqrt{\frac{\sum_{i=1}^N (x_i - x_i)^2}{N}} = \sqrt{0} = 0$$

## 9.3

MLE for Poisson distribution is  $\frac{\sum_{i=1}^N n_i}{N}$ .

(a)

Day 1:  $\frac{(3+1+4+2)}{4} = \frac{10}{4} = 2.5$  pop-ups per hour.

Day 2:  $\frac{(2+1+2)}{3} = \frac{5}{3} \approx 1.67$  pop-ups per hour.

Day 3:  $\frac{(3+2+2+1+4)}{5} = \frac{12}{5} = 2.4$  pop-ups per hour.

(b)

Day 4 MLE:  $\frac{13}{6} \approx 2.1$  pop-ups per hour.

(c)

MLE for all 4 days:

$$\frac{\# \text{ total pop-ups}}{\# \text{ total hours}} = \frac{40}{18} \approx 2.22 \text{ pop-ups per hour}$$

## 9.4

(a)

$$36 + \frac{36}{r}$$

(b)

Not very reliable because if on the very first spin the ball lands in a 0 slot, you would assume that all the slots are zeroes.

(c)

$$\frac{\left(\frac{36}{r_1} + \frac{36}{r_2} + \frac{36}{r_3}\right)}{3}$$

## 9.5

MLE for Binomial model is  $\Theta = \frac{k}{N}$ , where  $k$  is number of successes and  $N$  is number of draws.

(a)

$$\Theta_{blue} = \frac{0}{1} = 0$$

(b)

$$\Theta_{blue} = \frac{3}{10} = 0.3$$

## 9.7

(a)

$$\log \frac{P(y = 1 \mid x, \Theta)}{P(y = 0 \mid x, \Theta)} = x^T \Theta$$

$$\frac{P(y = 1 \mid x, \Theta)}{P(y = 0 \mid x, \Theta)} = e^{x^T \Theta}$$

$$P(y = 1 \mid x, \Theta) = P(y = 0 \mid x, \Theta) e^{x^T \Theta}$$

$$P(y = 1 \mid x, \Theta) = (1 - P(y = 1 \mid x, \Theta)) e^{x^T \Theta}$$

$$P(y = 1 \mid x, \Theta) = e^{x^T \Theta} - P(y = 1 \mid x, \Theta) e^{x^T \Theta}$$

$$P(y = 1 \mid x, \Theta) + P(y = 1 \mid x, \Theta) e^{x^T \Theta} = e^{x^T \Theta}$$

$$P(y = 1 \mid x, \Theta)(1 + e^{x^T \Theta}) = e^{x^T \Theta}$$

$$P(y = 1 \mid x, \Theta) = \frac{e^{x^T \Theta}}{1 + e^{x^T \Theta}}$$

(b)

$$\mathcal{L}(\Theta) = \prod_{i \in D} P(D \mid \Theta)$$

$$= \prod_{i \in D} P(y_i = 1 \mid x_i, \Theta)^{y_i} (1 - P(y_i = 1 \mid x_i, \Theta))^{1-y_i}$$

$$= \prod_{i \in D} \left( \frac{e^{x_i^T \Theta}}{1 + e^{x_i^T \Theta}} \right)^{y_i} \left( 1 - \frac{e^{x_i^T \Theta}}{1 + e^{x_i^T \Theta}} \right)^{1-y_i}$$

$$= \prod_{i \in D} \left( \frac{e^{x_i^T \Theta}}{1 + e^{x_i^T \Theta}} \right)^{y_i} \left( \frac{1}{1 + e^{x_i^T \Theta}} \right)^{1-y_i}$$

$$\log \mathcal{L}(\Theta) = \sum_{i \in D} y_i \log \left( \frac{e^{x_i^T \Theta}}{1 + e^{x_i^T \Theta}} \right) + (1 - y_i) \log \left( \frac{1}{1 + e^{x_i^T \Theta}} \right)$$

$$= \sum_{i \in D} y_i \log(e^{x_i^T \Theta}) - y_i \log(1 + e^{x_i^T \Theta}) + \log \left( \frac{1}{1 + e^{x_i^T \Theta}} \right) - y_i \log \left( \frac{1}{1 + e^{x_i^T \Theta}} \right)$$

$$\sum_{i \in D} y_i x_i^T \Theta - y_i \log(1 + e^{x_i^T \Theta}) + \log(1) - \log(1 + e^{x_i^T \Theta}) - y_i \log(1) + y_i \log(1 + e^{x_i^T \Theta})$$

$$= \sum_{i \in D} y_i x_i^T \Theta - \log(1 + e^{x_i^T \Theta})$$

(c)

$$\begin{aligned}\frac{\partial}{\partial \Theta} \mathcal{L}(\Theta) &= y_i x_i^T - \left[ x_i^T \cdot x_i^T \cdot \frac{1}{1 + e^{x_i^T \Theta}} \right] \\ &= x_i^T \left[ y_i - \frac{e^{x_i^T \Theta}}{1 + e^{x_i^T \Theta}} \right]\end{aligned}$$

Setting this derivative equal to zero and solving for  $\Theta$  will find the  $\Theta$  that maximizes  $\mathcal{L}(\Theta)$ .

## 9.9

(a)

- $P(n \mid z = 0) = 0$
- $P(n \mid z = 1) = \frac{1}{37}$
- $P(n \mid z = 2) = \frac{2}{38}$
- $P(n \mid z = 3) = \frac{3}{39}$

(b)

$P(z = 0 \mid \text{observations})$  is only non-zero if observations contains no data points that represent a bet not being payed out. Once a bet is not paid out, we know for a fact that the roulette wheel has more than 0 zero slots.

(c)

**z=0:**

$$P(z = 0 \mid \text{observations}) = 0 \text{ because a bet was not payed out } 2 > 0 \text{ times}$$

**z=1:**

$$P(z = 1 \mid \text{observations}) = \frac{P(z = 1)P(\text{observations} \mid z = 1)}{P(\text{observations})} = \frac{(0.2) \binom{36}{2} \left(\frac{1}{36}\right)^2 \left(\frac{35}{36}\right)^{34}}{P(\text{observations})} = \frac{0.03731}{P(\text{observations})}$$

**z=2:**

$$P(z = 2 \mid \text{observations}) = \frac{P(z = 2)P(\text{observations} \mid z = 2)}{P(\text{observations})} = \frac{(0.4) \binom{36}{2} \left(\frac{2}{36}\right)^2 \left(\frac{34}{36}\right)^{34}}{P(\text{observations})} = \frac{0.1114}{P(\text{observations})}$$

**z=3:**

$$P(z = 3 \mid \text{observations}) = \frac{P(z = 3)P(\text{observations} \mid z = 3)}{P(\text{observations})} = \frac{(0.3) \binom{36}{2} \left(\frac{3}{36}\right)^2 \left(\frac{33}{36}\right)^{34}}{P(\text{observations})} = \frac{0.068122}{P(\text{observations})}$$

$$\frac{0 + 0.03731 + 0.1114 + 0.068122}{P(observations)} = 1$$

$$\frac{0.21682}{P(observations)} = 1$$

$$P(observations) = 0.21682$$

$$P(z = 0 \mid observations) = \frac{0}{P(observations)} = 0$$

$$P(z = 1 \mid observations) = \frac{0.03731}{P(observations)} = 0.1721$$

$$P(z = 2 \mid observations) = \frac{0.1114}{P(observations)} = 0.5137$$

$$P(z = 3 \mid observations) = \frac{0.068122}{P(observations)} = 0.3142$$

Posterior for  $z = \{0, 1, 2, 3\} = \{0, 0.1721, 0.5137, 0.3142\}$