

# Mathematical statistics

## Homework 1

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### 1 Problem 1

$$f_i(x, y) = f_i(x)f_i(y), \quad (1)$$

Where

$$f_i(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp - \frac{(x - \mu_i)^2}{2\sigma^2} \quad (2)$$

Thus

$$f_i(x, y) = \frac{1}{2\sigma^2\pi} \exp - \frac{(x - \mu_i)^2 + (y - \mu_i)^2}{2\sigma^2} \quad (3)$$

Because  $x_i$  and  $y_i$  are two independent random values.

Maximum likelihood estimation of  $\sigma^2$ :

$$L = \prod_{i=1}^n f_i(x_i, y_i) \quad (4)$$

$$l = \ln \prod_{i=1}^n f_i(x_i, y_i) = \sum_{i=1}^n \ln f_i(x_i, y_i) = \quad (5)$$

$$= \sum_{i=1}^n \ln \frac{1}{2\pi\sigma^2} - \frac{(x_i - \mu_i)^2 + (y_i - \mu_i)^2}{2\sigma^2} \quad (6)$$

$$\frac{\partial l}{\partial \sigma^2} = \sum_{i=1}^n [\ln \frac{1}{2\pi\sigma^2}]' - ((x_i - \mu_i)^2 + (y_i - \mu_i)^2) [\frac{1}{2\sigma^2}]' \quad (7)$$

$$[\ln \frac{1}{2\pi\sigma^2}]' = 2\pi\sigma^2 [\frac{1}{2\pi\sigma^2}]' = -\frac{2\pi\sigma^2}{(2\pi\sigma^2)^2} [2\pi\sigma^2]' = -\frac{2\pi}{2\pi\sigma^2} = -\frac{1}{\sigma^2} \quad (8)$$

$$[\frac{1}{2\sigma^2}]' = -\frac{1}{4(\sigma^2)^2} [2\sigma^2]' = -\frac{2}{4(\sigma^2)^2} = -\frac{1}{2(\sigma^2)^2} \quad (9)$$

$$\frac{\partial l}{\partial \sigma^2} = \sum_{i=1}^n -\frac{1}{\sigma^2} + \frac{1}{2(\sigma^2)^2} ((x_i - \mu_i)^2 + (y_i - \mu_i)^2) = \quad (10)$$

$$= -\frac{n}{\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2) \quad (11)$$

Equating partial derivative to zero to obtain MLE of  $\sigma^2$ :

$$-\frac{n}{\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2) = 0 \quad (12)$$

$$\frac{n}{\sigma^2} = \frac{1}{2(\sigma^2)^2} \sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2) \quad (13)$$

$$\frac{2n\sigma^2}{2(\sigma^2)^2} = \frac{1}{2(\sigma^2)^2} \sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2) \quad (14)$$

$$2n\sigma^2 = \sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2) \quad (15)$$

$$\sigma^2 = \frac{\sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2)}{2n} \quad (16)$$

Taking partial derivative of  $l$  with respect to  $\mu_i$

$$\frac{\partial l}{\partial \mu_i} = -\frac{1}{2\sigma^2} [(x_i - \mu_i)^2 + (y_i - \mu_i)^2]' \quad (17)$$

$$[(x_i - \mu_i)^2 + (y_i - \mu_i)^2]' = -2(x_i - \mu_i) - 2(y_i - \mu_i) = -2(x_i + y_i - 2\mu_i) \quad (18)$$

$$\frac{\partial l}{\partial \mu_i} = \frac{1}{\sigma^2} (x_i + y_i - 2\mu_i) \quad (19)$$

Obtaining the system of equations:

$$\begin{cases} \sigma^2 = \frac{\sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2)}{2n} \\ \frac{1}{\sigma^2} (x_i + y_i - 2\mu_i) = 0 \end{cases} \quad (20)$$

$$\begin{cases} \sigma^2 = \frac{\sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2)}{2n} \\ x_i + y_i - 2\mu_i = 0 \end{cases} \quad (21)$$

$$\begin{cases} \sigma^2 = \frac{\sum_{i=1}^n ((x_i - \mu_i)^2 + (y_i - \mu_i)^2)}{2n} \\ \mu_i = \frac{x_i + y_i}{2} \end{cases} \quad (22)$$

$$\hat{\sigma}^2 = \frac{\sum_{i=1}^n ((x_i - \frac{x_i+y_i}{2})^2 + (y_i - \frac{x_i+y_i}{2})^2)}{2n} = \quad (23)$$

$$= \frac{\sum_{i=1}^n ((\frac{x_i-y_i}{2})^2 + (\frac{-x_i+y_i}{2})^2)}{2n} = \frac{\sum_{i=1}^n (\frac{1}{4}(x_i - y_i)^2 + \frac{1}{4}(-x_i + y_i)^2)}{2n} = \quad (24)$$

$$= \frac{\sum_{i=1}^n \frac{1}{4} 2(x_i - y_i)^2}{2n} = \frac{\sum_{i=1}^n (x_i - y_i)^2}{4n} \quad (25)$$

Proof of the inconsistency:

Let  $\xi_i = (x_i - y_i)$  for  $i = 1, \dots, n$ , let's check if our estimation is unbiased:

$$E \frac{1}{4n} \sum_{i=1}^n \xi_i^2 = \frac{1}{4n} E \sum_{i=1}^n \xi_i^2 = \frac{1}{4n} \sum_{i=1}^n E \xi_i^2 \quad (26)$$

$$E \xi_i^2 = D \xi_i + [E \xi_i]^2 \quad (27)$$

$$D \xi_i = D(x_i - y_i) = D x_i + (-1)^2 D y_i = 2\sigma^2 \quad (28)$$

$$[E \xi_i]^2 = [E(x_i - y_i)]^2 = [E x_i - E y_i]^2 = [\mu_i - \mu_i]^2 = 0 \quad (29)$$

$$E \xi_i^2 = 2\sigma^2 + 0 = 2\sigma^2 \quad (30)$$

$$\frac{1}{4n} \sum_{i=1}^n E \xi_i^2 = \frac{1}{4n} \sum_{i=1}^n 2\sigma^2 = \frac{2n\sigma^2}{4n} = \frac{\sigma^2}{2} \quad (31)$$

Our estimation of  $\sigma^2$  is biased. It is also asymptotically biased:

$$\lim_{n \rightarrow \infty} \frac{\sigma^2}{2} = \frac{\sigma^2}{2} \quad (32)$$

Consistent estimations can't be asymptotically biased. Thus our estimation is not consistent.

Q.E.D.

## 2 Problem 2

Let's make transition from Binomial distribution to Bernoulli distribution. Let:

$$a_i = \begin{cases} 1 & \text{In case } X_i \text{ contains at least one 1} \\ 0 & \text{otherwise} \end{cases} \quad (33)$$

$\gamma$  will be the parameter of such Bernoulli distribution, it is the probability of  $X_i$  containing at least one 1. Let's rewrite  $\gamma$  as a function of  $p$  and  $n_i$ , parameters of initial Binomial distribution:

$$\gamma = 1 - \binom{n_i}{0} p^0 (1-p)^{n_i} = 1 - (1-p)^{n_i} \quad (34)$$

Likelihood function:

$$L(\gamma) = \prod_{i=1}^n \gamma^{a_i} (1 - \gamma)^{1-a_i} \quad (35)$$

$$l(\gamma) = \sum_{i=1}^n \ln \gamma^{a_i} (1 - \gamma)^{1-a_i} = \sum_{i=1}^n a_i \ln \gamma + (1 - a_i) \ln 1 - \gamma \quad (36)$$

Substitute  $\gamma$  with the result of equation 34:

$$l(p) = \sum_{i=1}^n a_i \ln (1 - (1 - p)^{n_i}) + (1 - a_i) \ln (1 - 1 + (1 - p)^{n_i}) = \quad (37)$$

$$= \sum_{i=1}^n a_i \ln (1 - (1 - p)^{n_i}) + (1 - a_i) \ln (1 - p)^{n_i} \quad (38)$$

Taking derivative:

$$\frac{dl(p)}{dp} = \sum_{i=1}^n \frac{a_i n_i (1 - p)^{n_i - 1}}{(1 - (1 - p)^{n_i})} - \frac{(1 - a_i) n_i (1 - p)^{n_i - 1}}{(1 - p)^{n_i}} = \quad (39)$$

$$= \sum_{i=1}^n \frac{a_i n_i (1 - p)^{n_i - 1}}{(1 - (1 - p)^{n_i})} - \frac{(1 - a_i) n_i}{(1 - p)} \quad (40)$$

Equating to zero:

$$\sum_{i=1}^n \frac{a_i n_i (1 - p)^{n_i - 1}}{(1 - (1 - p)^{n_i})} - \frac{(1 - a_i) n_i}{(1 - p)} = 0 \quad (41)$$

$$\sum_{i=1}^n \frac{a_i n_i (1 - p)^{n_i - 1}}{(1 - (1 - p)^{n_i})} = \sum_{i=1}^n \frac{(1 - a_i) n_i}{(1 - p)} \quad (42)$$

$$(1 - p) \sum_{i=1}^n \frac{a_i n_i (1 - p)^{n_i - 1}}{(1 - (1 - p)^{n_i})} = \sum_{i=1}^n (1 - a_i) n_i \quad (43)$$

$$\sum_{i=1}^n \frac{a_i n_i (1 - p)^{n_i}}{(1 - (1 - p)^{n_i})} = \sum_{i=1}^n (1 - a_i) n_i \quad (44)$$

Proving that likelihood function has 1 root:

In the left part of equation 43 we have a positive constant value or zero. To

investigate right part's behaviour lets take it's derivative with respect to  $p$ :

$$\frac{df(p)}{dp} = \sum_{i=1}^n a_i n_i \frac{-n_i(1-p)^{n_i-1}(1-(1-p)^{n_i}) - (1-p)^{n_i} n_i (1-p)^{n_i-1}}{(1-(1-p)^{n_i})^2} = \quad (45)$$

$$= \sum_{i=1}^n a_i n_i \frac{-n_i((1-p)^{n_i-1} - (1-p)^{2n_i-1} + (1-p)^{2n_i-1})}{(1-(1-p)^{n_i})^2} = \quad (46)$$

$$= \sum_{i=1}^n a_i n_i \frac{-n_i(1-p)^{n_i-1}}{(1-(1-p)^{n_i})^2} = - \sum_{i=1}^n a_i n_i^2 \frac{(1-p)^{n_i-1}}{(1-(1-p)^{n_i})^2} \quad (47)$$

Since  $p \in [0, 1]$  the expression we obtained has negative value for every  $p$  except for  $p = 1$  where it is equal zero. Negative derivative means that our function is monotonically decreasing.

Now let's find the range of values of the right part:

$$\lim_{p \rightarrow 0} \sum_{i=1}^n \frac{a_i n_i (1-p)^{n_i}}{(1-(1-p)^{n_i})} = \infty \quad (48)$$

$$\lim_{p \rightarrow 1} \sum_{i=1}^n \frac{a_i n_i (1-p)^{n_i}}{(1-(1-p)^{n_i})} = 0 \quad (49)$$

Earlier we've already established that left part of equation 44 is a positive constant value or zero. And since right part is monotonically decreasing function on  $[0, 1]$  with the range of values  $[0, \infty]$  it the equation has one root.

Q.E.D.