

IDSSMA

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## IDSSM

1. ~~part~~ a.  $\therefore P(y; \pi) = \pi^y (1-\pi)^{1-y}$

$$\therefore \text{Pdf } f(y) = \begin{cases} \pi & y=1 \\ 1-\pi & y=0. \end{cases}$$

$$E(Y) = 1 \times \pi + 0 \times (1-\pi) = \pi$$

$$\begin{aligned} \text{Var}(Y) &= (0 - E(Y))^2 \cdot p_0 + (1 - E(Y))^2 \cdot p_1 \\ &= \pi^2 (1-\pi) + (1-\pi)^2 \cdot \pi \\ &= \pi^2 - \pi^3 + \pi - 2\pi^2 + \pi^3 \\ &= \pi - \pi^2. \end{aligned}$$

$$\therefore E(Y) = \pi \quad \text{Var}(Y) = \pi - \pi^2 = \pi(1-\pi)$$

b. according to a, we have

$$E(Y) = \pi.$$

$$\therefore \hat{\pi} = \bar{Y}$$

$$E(\hat{\pi}) = E(\bar{Y}) = E\left(\frac{\sum_{i=1}^n Y_i}{n}\right) = \frac{1}{n} \times E(\sum Y_i) = \frac{n\pi}{n} = \pi.$$

So,  $\pi$  is unbiased estimate

C. the method-of-moments estimate of  $\pi$  is  $\bar{Y}$

$$\text{and } MSE(\bar{\pi}) = \text{Var}(\bar{\pi}) + \text{Bias}(\hat{\pi}, \pi)^2$$

Because the  $\bar{\pi}$  is unbiased.

$$\therefore MSE(\bar{\pi}) = \text{Var}(\bar{\pi}) = \text{Var}(\bar{Y})$$

$$= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(Y_i) = \frac{\pi(1-\pi)}{n}$$

$$\therefore MSE = \frac{\pi(1-\pi)}{n}$$

d. estimator:  $\text{Var}(Y) = \pi(1-\pi)$

$$E[\text{Var}(Y)] = E(\pi - \pi^2)$$

$$= E(\pi) - E(\pi^2)$$

$$= E(\bar{\pi}) - [ \text{Var}(\bar{\pi}) + E^2(\bar{\pi}) ]$$

before  
as above, we know.

$$E(\bar{\pi}) = \pi, \quad \text{Var}(\bar{\pi}) = \frac{\pi(1-\pi)}{n}$$

$$\therefore E[\text{Var}(Y)] = \pi - \frac{\pi(1-\pi)}{n} - \pi^2$$

$$= \frac{n-1}{n} \cdot \pi(1-\pi) \neq \pi(1-\pi)$$

this is ~~not~~ biased. in tend to make it unbiased.

$$\frac{n}{n-1} \cdot E[\text{Var}(Y)] = \pi(1-\pi).$$

the unbiased estimator is  $\frac{n}{n-1} \text{Var}(Y)$ .

$$\text{is } \frac{n}{n-1} \cdot (1-\pi) \cdot \pi = \frac{n}{n-1} \bar{Y} (1-\bar{Y})$$

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library(tidyverse)
titanic <- read.csv("titanic.csv")

titanic <- select(titanic, survived, gender, pclass)

male <- filter(titanic, gender == "male")

female <- filter(titanic, gender == "female")

firstclass.male <- filter(male, pclass == 1)
firstclass.female <- filter(female, pclass == 1)

msur <- sum(male$survived)/length(male$survived);msur

## [1] 0.1909846

fsur <- sum(female$survived)/length(female$survived);fsur

## [1] 0.7274678

firstclass.msur <- sum(firstclass.male$survived)/length(firstclass.male$survived)
firstclass.fsur <- sum(firstclass.female$survived)/length(firstclass.female$survived)
firstclass.fsur

## [1] 0.9652778

firstclass.msur

## [1] 0.3407821

```

The male survived rate is 0.19, female survived rate is 0.73. In 1st class male survived rate is 0.34, female survived rate is 0.96

2. the Poisson distribution's pmf:  $\frac{\lambda^k e^{-\lambda}}{k!}$

So we get likelihood function:

$$L_k(\lambda) = \prod_{i=1}^n \frac{\lambda^{k_i} \cdot e^{-\lambda}}{k_i!}$$

$$\ln L_k(\lambda) = \sum_{i=1}^n \ln \lambda^{k_i} + \sum_{i=1}^n \ln e^{-\lambda} - \sum_{i=1}^n \ln(k_i!)$$

$$\ln L_k(\lambda) = \ln \lambda \cdot \sum_{i=1}^n k_i + (0 - n\lambda) - \sum_{i=1}^n \ln(k_i!)$$

$$(\ln L_k(\lambda))' = \frac{\sum_{i=1}^n k_i}{\lambda} - n$$

$$\text{Let } (\ln L_k(\lambda))' = 0.$$

$$\lambda = \frac{\sum_{i=1}^n k_i}{n} = \bar{k}$$

$\therefore$  the maximum likelihood estimate of  $\lambda$  is

$$\lambda = \bar{k} = 1.5$$