

STAT 417 Lecture Note 8

E.g. 4.

Multinomial distribution: Suppose $X_1, X_2, \dots, X_k$ are ~~integer valued~~ random variables such that $X_1 + X_2 + \dots + X_k = n$, where n is a deterministic integer.

We say that $(X_1, X_2, \dots, X_k)$ follows multinomial distribution, with parameters $\theta = (\theta_1, \theta_2, \dots, \theta_k)$, if the ~~probability~~ distribution function of $(X_1, X_2, \dots, X_k)$ is

$$f_{\theta}(x_1, \dots, x_k) = \binom{n}{x_1, x_2, \dots, x_k} \theta_1^{x_1} \theta_2^{x_2} \dots \theta_k^{x_k}.$$

E.g. when $k=3$, $x_1=2$, $x_2=3$, $x_3=4$, $n=9$.

$$\text{then } f_{\theta}(x_1, x_2, x_3) = \binom{9}{2, 3, 4} \theta_1^2 \theta_2^3 \theta_3^4.$$

multinomial model, and likelihood function. parameter space is

$$\Theta = \{(\theta_1, \dots, \theta_k) \mid 0 \leq \theta_1, \dots, \theta_k \leq 1, \theta_1 + \dots + \theta_k = 1\}.$$

Suppose samples are $(X_1, \dots, X_k) \sim \text{multinomial}(n; \theta_1, \theta_2, \dots, \theta_k)$.

Then the likelihood function is

$$L(\theta \mid x_1, x_2, \dots, x_k) = f_{\theta}(x_1, x_2, \dots, x_k) = \binom{n}{x_1, \dots, x_k} \theta_1^{x_1} \theta_2^{x_2} \dots \theta_k^{x_k}.$$

$$\text{so } \ell(\theta \mid x_1, \dots, x_k) = \log L(\theta \mid x_1, \dots, x_k) = \log \binom{n}{x_1, \dots, x_k} + x_1 \log \theta_1 + \dots + x_k \log \theta_k.$$

~~$$\frac{\partial \ell(\theta \mid x_1, \dots, x_k)}{\partial \theta_1} = \log \binom{n}{x_1, \dots, x_k} + x_1 \log \theta_1 + \dots + x_{k-1} \log \theta_{k-1} + x_k \log (1 - \theta_1 - \theta_2 - \dots - \theta_{k-1})$$~~
~~$$\frac{\partial \ell(\theta \mid x_1, \dots, x_k)}{\partial \theta_2} = \log \binom{n}{x_1, \dots, x_k} + x_1 \log \theta_1 + \dots + x_{k-1} \log \theta_{k-1} + x_k \log (1 - \theta_1 - \theta_2 - \dots - \theta_{k-1})$$~~
~~$$\vdots$$~~
~~$$\frac{\partial \ell(\theta \mid x_1, \dots, x_k)}{\partial \theta_k} = \log \binom{n}{x_1, \dots, x_k} + x_1 \log \theta_1 + \dots + x_{k-1} \log \theta_{k-1} + x_k \log (1 - \theta_1 - \theta_2 - \dots - \theta_{k-1})$$~~

$$\text{So } \frac{\partial}{\partial \theta_1} \ell(\theta | x_1, \dots, x_k) = \frac{x_1}{\theta_1} - \frac{x_k}{1 - \theta_1 - \theta_2 - \dots - \theta_{k-1}} = 0$$

$$\frac{\partial}{\partial \theta_2} \ell(\theta | x_1, \dots, x_k) = \frac{x_2}{\theta_2} - \frac{x_k}{1 - \theta_1 - \theta_2 - \dots - \theta_{k-1}} = 0$$

⋮

$$\frac{\partial}{\partial \theta_{k-1}} \ell(\theta | x_1, \dots, x_k) = \frac{x_{k-1}}{\theta_{k-1}} - \frac{x_k}{1 - \theta_1 - \theta_2 - \dots - \theta_{k-1}} = 0.$$

solving these equations, we get $\frac{x_1}{\theta_1} = \frac{x_2}{\theta_2} = \dots = \frac{x_{k-1}}{\theta_{k-1}} = \frac{x_k}{1 - \theta_1 - \theta_2 - \dots - \theta_{k-1}}$

$$\theta_1 = \frac{x_1}{n}, \quad \theta_2 = \frac{x_2}{n}, \quad \dots, \quad \theta_k = \frac{x_k}{n}.$$

$$\text{So } \hat{\theta}_{ML} = \left(\frac{x_1}{n}, \frac{x_2}{n}, \dots, \frac{x_k}{n} \right).$$

E.g. 5. If x_1, x_2 are iid samples from $\text{unif}(0, \theta)$.

~~find~~ find ① $L(\theta | x_1, x_2)$, ② $\hat{\theta}_{ML}$.

$$\text{① } L(\theta | x_1, x_2) = f_\theta(x_1, x_2) = f_\theta(x_1) f_\theta(x_2).$$

recall for $\text{unif}(0, \theta)$, the pdf is

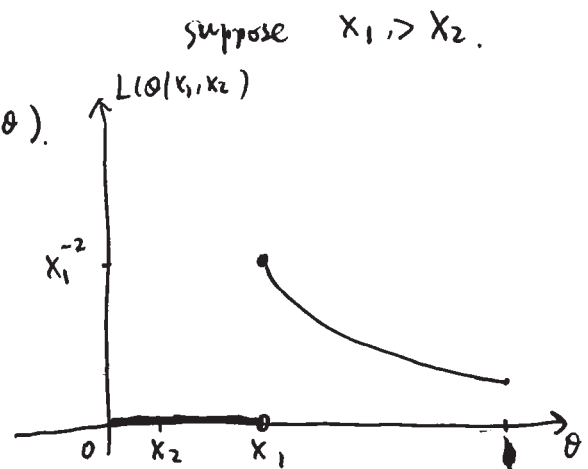
$$f_\theta(x) = \begin{cases} \frac{1}{\theta}, & \text{if } 0 \leq x \leq \theta, \\ 0, & \text{o/w.} \end{cases}$$

using indicator, we rewrite $f_\theta(x) = \frac{1}{\theta} \mathbb{1}(0 \leq x \leq \theta)$.

$$\text{So } L(\theta | x_1, x_2) = \frac{1}{\theta^2} \mathbb{1}(0 \leq x_1 \leq \theta) \cdot \mathbb{1}(0 \leq x_2 \leq \theta).$$

$$= \frac{1}{\theta^2} \mathbb{1}(\theta \geq \max\{x_1, x_2\}).$$

$$\hat{\theta}_{ML} = \max\{x_1, x_2\}.$$



plug-in ^{MLE} ~~MLE~~ estimation.

If we want to estimate ~~the~~ $\eta = \gamma(\theta)$, a function of θ ,
and we have obtained $\hat{\theta}_{ML}$, then a ~~plug-in estimator for~~ ~~estimated~~
natural estimation of η is

$$\hat{\eta} = \gamma(\hat{\theta}_{ML}).$$

$\hat{\eta}$ is called a plug-in ^{estimation} ~~MLE~~ of η .

Ex. 6. For $X_1, X_2, \dots, X_n$ iid from $N(\mu, \sigma^2)$.

$$\hat{\mu}_{ML} = \bar{X}, \quad \hat{\sigma}_{ML}^2 = \frac{n-1}{n} s^2.$$

then the plug-in _{MLE} estimation of e^{μ} is $e^{\bar{X}}$.

the plug-in MLE of σ is $\sqrt{\frac{n-1}{n} s^2}$.