

## &lt; Beta distribution &gt;

Beta (a, b)

$$f(y) = \begin{cases} \frac{1}{B(a, b)} y^{a-1} (1-y)^{b-1}, & 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$$

상수처럼

$$B(a, b) = \begin{cases} \frac{\Gamma(a) \Gamma(b)}{\Gamma(a+b)} \\ \int_0^1 x^{a-1} (1-x)^{b-1} dx \end{cases}$$

$$\Gamma(a) = \int_0^\infty x^{a-1} e^{-x} dx$$

$$E(Y) = \frac{a}{a+b}, \quad \text{Var}(Y) = \frac{ab}{(a+b)^2(a+b+1)}$$

$$\int_0^1 y \cdot \frac{1}{B(a, b)} y^{a-1} (1-y)^{b-1} dy = \frac{1}{B(a, b)} \int_0^1 y^a (1-y)^{b-1} dy$$

$B(a+1, b)$

$$= \frac{B(a+1, b)}{B(a, b)}$$

$$\Gamma(a) = (a-1)!$$

개념이 중요!!

## ★ &lt; MLE (Maximum Likelihood Estimator) &gt;

ex)  $Y_1, \dots, Y_n \stackrel{iid}{\sim} \text{Poisson}(\lambda)$ ① MLE of  $\lambda \rightarrow$  parameter가 중요② MLE of  $\lambda^{-1}$ 

$$f(y|\lambda) = \frac{e^{-\lambda} \cdot \lambda^y}{y!}$$

$$\textcircled{1} \quad L(\lambda) = \prod_{i=1}^n \frac{e^{-\lambda} \lambda^{y_i}}{y_i!}$$

$$= \frac{e^{-n\lambda} \lambda^{\sum y_i}}{\prod_{i=1}^n y_i!}$$

$$\ln L(\lambda) = -n\lambda + \sum y_i \ln \lambda - \ln \left( \prod_{i=1}^n y_i! \right)$$

$$\frac{\partial}{\partial \lambda} \ln L(\lambda) = -n + \frac{\sum y_i}{\lambda} \stackrel{\text{set}}{=} 0$$

$$\Rightarrow \hat{\lambda} = \frac{1}{n} \sum_{i=1}^n y_i = \bar{y}$$

$$\hat{\lambda}^{\text{MLE}} = \bar{y}$$

$$\Rightarrow \frac{\partial^2}{\partial \lambda^2} \ln L(\lambda) = -\frac{\sum y_i}{\lambda^2} < 0$$

② MLE of  $e^{-\lambda}$

i) set  $\alpha = e^{-\lambda}$

MLE of  $\alpha$ ?

$$L(\lambda) = \frac{e^{-n\lambda} \cdot \lambda^{\sum y_i}}{\prod_{i=1}^n y_i!}$$

$\alpha = e^{-\lambda}$

$$L(\alpha) = \frac{\alpha^n \cdot (-\ln \alpha)^{\sum y_i}}{\prod_{i=1}^n y_i!}$$

$$\ln L(\alpha)$$

$$\frac{\partial}{\partial \alpha} \ln L(\alpha) = \stackrel{\text{set}}{=} 0$$

ii) by **invariance property** of MLE,  
MLE of  $e^{-\lambda}$  is  $e^{-\bar{y}}$

### \*\*\* < Large Sample Properties of MLE >

$Y_1, \dots, Y_n \stackrel{iid}{\sim} f(y|\theta)$

(a)  $\hat{\theta}_n^{MLE} \xrightarrow{P} \theta$

(b)  $\hat{\theta}_n^{MLE} \xrightarrow{D} N\left(\theta, \frac{1}{nI(\theta)}\right)$  (CLT)  
approximate distribution  
asymptotic variance of MLE

(c)  $I(\theta) = E\left[-\frac{\partial^2}{\partial \theta^2} \ln f(Y|\theta)\right]$

\*\*\*  
<  $\hat{\theta}^{MLE}$  이용해 CI of  $\theta$  구하기 >  
 $\Rightarrow$  CLT, Slutsky 이용

ex)  $Y_1, \dots, Y_n \sim \exp(\theta)$

•  $\hat{\theta}^{MLE} = \bar{y}$

•  $I(\theta) = E\left[-\frac{\partial^2}{\partial \theta^2} \ln f(Y|\theta)\right] = \frac{1}{\theta^2}$

•  $\hat{\theta}^{MLE} \xrightarrow{D} N\left(\theta, \frac{\theta^2}{n}\right)$

• 95% CI of  $\theta$ ?

① MLE로  $N(0,1)$  만들기

$$\frac{\hat{\theta}^{MLE} - E(\hat{\theta}^{MLE})}{\sqrt{\text{Var}(\hat{\theta}^{MLE})}} \xrightarrow{D} N(0,1) \quad \text{by CLT}$$

$$\frac{\bar{Y} - \theta}{\frac{\theta}{\sqrt{n}}} \xrightarrow{D} N(0,1) \quad \text{by CLT}$$

$$\textcircled{2} P(-1.96 < \frac{\bar{Y} - \theta}{\theta/\sqrt{n}} < 1.96) = 95\%$$

$$\textcircled{3} \frac{\bar{Y} - \theta}{\frac{\hat{\theta}^{MLE}}{\sqrt{n}}} \xrightarrow{D} N(0,1)$$

Yes 이면  
새로운 pivotal quantity로 사용

$\Rightarrow$  Slutsky

$$\frac{\frac{\bar{Y} - \theta}{\theta/\sqrt{n}}}{\frac{\hat{\theta}^{MLE}}{\theta}} \xrightarrow{D} N(0,1) = \frac{\bar{Y} - \theta}{\frac{\hat{\theta}^{MLE}}{\sqrt{n}}} \xrightarrow{D} N(0,1)$$

$$\hat{\theta}^{MLE} \xrightarrow{P} \theta$$

$$\frac{\hat{\theta}^{MLE}}{\theta} \xrightarrow{P} 1$$

$$\textcircled{4} P\left(-1.96 < \frac{\bar{Y} - \theta}{\frac{\hat{\theta}^{MLE}}{\sqrt{n}}} < 1.96\right) = 0.95$$

<  $L(\theta)$  가 미분 불가능일 때 >

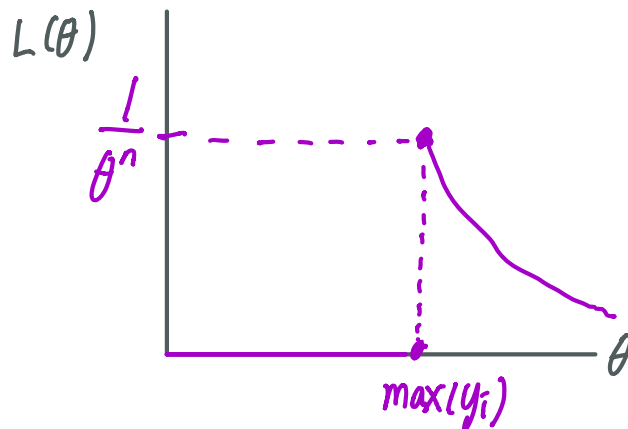
ex)  $Y_1, \dots, Y_n \sim \text{Unif}(0, \theta)$

$$L(\theta) = \prod_{i=1}^n \frac{1}{\theta} I_{(0, \theta)}(y_i)$$

$$= \frac{1}{\theta^n} \cdot I_{(\max y_i, \infty)}(\theta)$$

$\frac{\partial}{\partial \theta} L(\theta)$  불가능 Indicator가  $\theta$ 에 dependent

↓  
plot 그리기



$\therefore$  Likelihood  $L(\theta)$ 를 maximize 하는  $\hat{\theta}^{MLE} = \max(y_i)$