

# Transformation of parameters: the likelihood

- We will look at the invariance property of MLE in this and the next two videos
- If we transform the parameter from  $\theta$  to  $\phi = \Phi(\theta)$ , the value of the likelihood remains the same (provided the transformation is one-to-one)
- This means we can obtain the MLE of  $\phi$  by applying the transformation to  $\theta$ , i.e.  $\hat{\phi} = \Phi(\hat{\theta})$

# Setup

Suppose  $y_1, y_2, \dots, y_n$  are independent observations with log-likelihood  $\ell(\theta; \mathbf{Y})$ , for a scalar parameter  $\theta$ .

Consider an invertible, twice differentiable function  $\Phi$ .

Taking  $\phi = \Phi(\theta)$  we can take  $\phi$  as the parameter of interest rather than  $\theta$ .

e.g.  $Y_1, Y_2, \dots, Y_n \sim \text{iid Ber}(\theta)$

log-odds  $\phi = \log\left(\frac{\theta}{1-\theta}\right) = \bar{\Phi}(\theta)$

# Relationship between likelihoods

Let the log-likelihoods with respect to  $\theta$  and  $\phi$  be given respectively by

$$\underline{\ell_{\theta}(\theta; \mathbf{y})} \text{ and } \underline{\ell_{\phi}(\phi; \mathbf{y})}.$$

As  $\Phi$  is invertible,

$$\theta = \Phi^{-1}(\phi)$$

It can be checked that the two likelihood are related by

$$\ell_{\phi}(\phi; \mathbf{y}) = \underline{\ell_{\theta}(\Phi^{-1}(\phi); \mathbf{y})}$$

and

$$\ell_{\theta}(\theta; \mathbf{y}) = \underline{\ell_{\phi}(\Phi(\theta; \mathbf{y}))}.$$

# Example 5.12

Suppose  $y_1, y_2, \dots, y_n$  are *i.i.d.* Bernoulli observations with probability  $\theta$ .

Consider the log-odds,  $\Phi(\theta) = \log\left(\frac{\theta}{1-\theta}\right)$ .

Calculate the log-likelihoods for both parameterizations.

Check that  $l_\phi(\phi; y) = l_\theta(\Phi^{-1}(\phi); y)$ .

$\theta$  form

$$p(y_i; \theta) = \theta^{y_i} (1-\theta)^{1-y_i}, \quad y_i = 0, 1$$
$$L(\theta; y) = \prod_{i=1}^n p(y_i; \theta) = \prod_{i=1}^n \theta^{y_i} (1-\theta)^{1-y_i} = \theta^{\sum_{i=1}^n y_i} (1-\theta)^{n - \sum_{i=1}^n y_i}$$
$$l(\theta; y) = \left(\sum_{i=1}^n y_i\right) \log \theta + \left(n - \sum_{i=1}^n y_i\right) \log (1-\theta)$$

$\phi$  form

$$\phi = \log\left(\frac{\theta}{1-\theta}\right)$$
$$e^\phi = \frac{\theta}{1-\theta}$$
$$(1-\theta)e^\phi = \theta$$
$$e^\phi - \theta e^\phi = \theta$$
$$\Rightarrow \theta = \frac{e^\phi}{1+e^\phi} = \Phi^{-1}(\phi)$$

# Example 5.12 Solution

$$p(y; \phi) = \left( \frac{e^\phi}{1+e^\phi} \right)^{y_i} \left( 1 - \frac{e^\phi}{1+e^\phi} \right)^{1-y_i} = \left( \frac{e^\phi}{1+e^\phi} \right)^{y_i} \left( \frac{1}{1+e^\phi} \right)^{1-y_i}$$

$$L(\phi; y) = \left( \frac{e^\phi}{1+e^\phi} \right)^{\sum_{i=1}^n y_i} \left( \frac{1}{1+e^\phi} \right)^{n - \sum_{i=1}^n y_i}$$

$$\ell(\phi; y) = \left( \sum_{i=1}^n y_i \right) \log \left( \frac{e^\phi}{1+e^\phi} \right) + \left( n - \sum_{i=1}^n y_i \right) \log \left( \frac{1}{1+e^\phi} \right)$$

$$= \left( \sum_{i=1}^n y_i \right) \log (\bar{\Phi}(\phi)) + \left( n - \sum_{i=1}^n y_i \right) \log (1 - \bar{\Phi}(\phi))$$

$$= \ell(\bar{\Phi}(\phi); y)$$

# Theorem 15

Suppose  $\ell_{\theta}(\theta; \mathbf{y})$  and  $\ell_{\phi}(\phi; \mathbf{y})$  are equivalent parametrizations of the same problem. Then

$$\hat{\phi} = \Phi(\hat{\theta}).$$

This property is called the invariance property of MLE.

Proof:

Observe that the possible values of  $\phi$  are  $\{\phi: \phi = \Phi(\theta), \theta \in \Theta\}$ .

Recall that  $\ell_{\phi}(\Phi(\theta); \mathbf{y}) = \ell_{\theta}(\theta; \mathbf{y})$

Maximizing  $\ell_{\phi}(\phi; \mathbf{y})$  wrt  $\phi$

$\ell_{\phi}(\Phi(\theta); \mathbf{y})$

$\ell_{\theta}(\theta; \mathbf{y})$  wrt  $\theta$

Hence  $\hat{\phi} = \Phi(\hat{\theta})$ .

# Example 5.13

Suppose  $y_1, y_2, \dots, y_n$  are *i.i.d.* Bernoulli observations with probability  $\theta$ .

Consider the log-odds,  $\Phi(\theta) = \log\left(\frac{\theta}{1-\theta}\right)$ .

Find the MLE of  $\theta$ . What is the MLE of  $\phi$ ?

$$\ell(\theta; \mathbf{y}) = \left(\sum_{i=1}^n y_i\right) \log \theta + \left(n - \sum_{i=1}^n y_i\right) \log(1-\theta)$$

$$S(\theta; \mathbf{y}) = \frac{1}{\theta} \left(\sum_{i=1}^n y_i\right) - \left(\frac{1}{1-\theta}\right) \left(n - \sum_{i=1}^n y_i\right) = 0$$

$$\frac{1}{\theta} \left(\sum_{i=1}^n y_i\right) = \left(\frac{1}{1-\theta}\right) \left(n - \sum_{i=1}^n y_i\right)$$

By Theorem 15,

$$\hat{\phi} = \Phi(\hat{\theta})$$

$$= \log\left(\frac{\hat{\theta}}{1-\hat{\theta}}\right)$$

$$= \log\left(\frac{\bar{y}}{1-\bar{y}}\right)$$

$$\left(\frac{1-\theta}{\theta}\right) \left(\sum_{i=1}^n y_i\right) = n - \sum_{i=1}^n y_i$$

$$\left(\frac{1}{\theta} - 1\right) \left(\sum_{i=1}^n y_i\right) = n - \sum_{i=1}^n y_i$$

$$\frac{1}{\theta} \sum_{i=1}^n y_i - \sum_{i=1}^n y_i = n - \sum_{i=1}^n y_i$$

$$\frac{1}{\theta} \sum_{i=1}^n y_i = n$$

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

Exercise: Check that the MLE of  $\phi$  derived directly using  $\ell_{\phi}(\phi; \mathbf{y})$  is the same as what we have here.

We can check that  $\hat{\phi} = \log\left(\frac{\bar{y}}{1-\bar{y}}\right)$  by deriving the MLE of  $\phi$  using the alternative parametrization with  $\phi$ .

$$\begin{aligned}\ell(\phi; \mathbf{y}) &= \left(\sum_{i=1}^n y_i\right) \log\left(\frac{e^{\phi}}{1+e^{\phi}}\right) + \left(n - \sum_{i=1}^n y_i\right) \log\left(\frac{1}{1+e^{\phi}}\right) \\&= \left(\sum_{i=1}^n y_i\right) \log(e^{\phi}) - \left(\sum_{i=1}^n y_i\right) \log(1+e^{\phi}) - \left(n - \sum_{i=1}^n y_i\right) \log(1+e^{\phi}) \\&= \left(\sum_{i=1}^n y_i\right) \phi - n \log(1+e^{\phi}) \\&= n\bar{y}\phi - n \log(1+e^{\phi})\end{aligned}$$

Solving  $S(\phi; \mathbf{y}) = n\bar{y} - n\left(\frac{e^{\phi}}{1+e^{\phi}}\right) = 0$  for  $\phi$  gives

$$\hat{\phi} = \log\left(\frac{\bar{y}}{1-\bar{y}}\right).$$