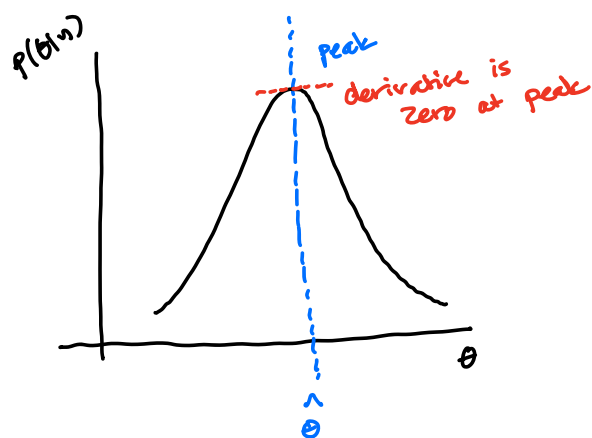


$$p(\theta|y) \propto \exp(a\theta^2 + b\theta + c)$$

$$\log(p(\theta|y)) \propto a\theta^2 + b\theta + c$$



$$\left. \frac{d}{d\theta} \log[p(\theta|y)] \right|_{\theta=\hat{\theta}} = 0$$

θ is likely to be multidimensional

$$f(\theta) \approx f(\theta_0) + \nabla f(\theta_0)^T (\theta - \theta_0) + \frac{1}{2} (\theta - \theta_0)^T H f(\theta_0) (\theta - \theta_0)$$

$$\log(p(\theta|y)) \approx \log p(\hat{\theta}|y) + 0 + \frac{1}{2} (\theta - \hat{\theta})^T \left[\frac{d^2}{(d\theta)^2} \log p(\theta|y) \right]_{\theta=\hat{\theta}} (\theta - \hat{\theta})$$

observed Fisher information

$$I(\theta) = - \frac{\partial^2}{\partial \theta^2} \log p(\theta|y)$$

$$\log(p(\theta|y)) \approx \log p(\hat{\theta}|y) + 0 + \frac{1}{2}(\theta - \hat{\theta})^T \left[\frac{d^2}{(d\theta)^2} \log p(\theta|y) \right]_{\theta=\hat{\theta}} (\theta - \hat{\theta})$$

$$\log p(\theta|y) \approx A + \frac{1}{2}(\theta - \hat{\theta})^T I(\theta) (\theta - \hat{\theta})$$

$$p(\theta|y) \approx B e^{\frac{1}{2}(\theta - \hat{\theta})^T I(\theta) (\theta - \hat{\theta})}$$

multiparameter normal distribution

$$p(\theta|y) \approx N(\hat{\theta}, I(\theta)^{-1})$$

Example: normal distribution with unknown and unknown variance

Prior: noninformative prior $p(\mu, \sigma^2) \propto \frac{1}{\sigma^2}$

show $p(\mu, \log \sigma) \propto 1$

$$(\mu, \sigma^2) \mapsto (\mu, \log \sigma)$$

$$J = \begin{pmatrix} \frac{\partial \mu}{\partial \mu} & \frac{\partial \mu}{\partial \log \sigma} \\ \frac{\partial \sigma^2}{\partial \mu} & \frac{\partial \sigma^2}{\partial \log \sigma} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 2\sigma^2 \end{pmatrix}$$

$$\hookrightarrow \sigma^2 = e^{2 \log \sigma}$$

$$\frac{\partial e^{2 \log \sigma}}{\partial \log \sigma} = 2 e^{2 \log \sigma} = 2\sigma^2$$

$$|J| = 2\sigma^2 \quad \text{so} \quad p(\mu, \log \sigma) = p(\mu, \sigma^2) \cdot |J| \propto \frac{1}{\sigma^2} \cdot 2\sigma^2 = 2 \propto 1$$

① $\theta = (\mu, \log \sigma)$ so our noninformative prior is $p(\mu, \log \sigma) = 1$

② Find $\hat{\theta}$.

Need to find the peak of $p(\mu, \log \sigma | y)$

Recall from module 3:

$$p(\mu, \log \sigma | y) \propto \sigma^{-n} \exp \left(-\frac{1}{2\sigma^2} \left[(n-1)s^2 + n(\bar{y} - \mu)^2 \right] \right)$$

due to [3]

$$\log(p(\mu, \log \sigma | y)) \propto -n \log \sigma - \frac{1}{2\sigma^2} \left[(n-1)s^2 + n(\bar{y} - \mu)^2 \right]$$

this is the function around which we will construct our Taylor series

$\hat{\theta}$ is the point where $\nabla \log(p(\mu, \log \sigma | y)) = \vec{0}$

$$\frac{\partial}{\partial \mu} \log(p(\mu, \log \sigma | y)) \propto \frac{n(\bar{y} - \mu)}{\sigma^2} = 0$$

$$\sigma^{-2} = e^{-2 \log \sigma}$$

$$\frac{\partial}{\partial \log \sigma} \log(p(\mu, \log \sigma | y)) \propto -n + \frac{(n-1)s^2 + n(\bar{y} - \mu)^2}{\sigma^2} = 0$$

$$\frac{n(\bar{y} - \mu)}{\sigma^2} = 0 \Rightarrow n(\bar{y} - \mu) = 0 \Rightarrow \boxed{\bar{y} = \mu} = \hat{\theta},$$

$$-n + \frac{(n-1)s^2 + n(\bar{y} - \mu)^2}{\sigma^2} = 0 \Rightarrow \frac{-n\sigma^2 + (n-1)s^2}{\sigma^2} = 0$$

$$\Rightarrow (n-1)s^2 = n\sigma^2$$

$$\Rightarrow \left[\frac{(n-1)s^2}{n} = \sigma^2 \right] \neq \hat{\theta}_2$$

$$2 \log \sigma = \log \left(\frac{(n-1)s^2}{n} \right)$$

$$\Rightarrow \boxed{\log \sigma = \frac{1}{2} \log \left(\frac{(n-1)s^2}{n} \right)} \quad \parallel \quad \hat{\theta}_2$$

$$\hat{\theta} = \begin{pmatrix} \bar{y} \\ \frac{1}{2} \log \left(\frac{(n-1)s^2}{n} \right) \end{pmatrix}$$

③ Find $I(\hat{\theta})$.

$$\log(p(\mu, \log \sigma | y)) \propto -n \log \sigma - \frac{1}{2\sigma^2} [(n-1)s^2 + n(\bar{y} - \mu)^2]$$

$$\frac{\partial}{\partial \mu} \log(p(\mu, \log \sigma | y)) \propto \frac{n(\bar{y} - \mu)}{\sigma^2}$$

$$\frac{\partial}{\partial \log \sigma} \log(p(\mu, \log \sigma | y)) \propto -n + \frac{(n-1)s^2 + n(\bar{y} - \mu)^2}{\sigma^2}$$

$$\frac{\partial^2}{(\partial \mu)^2} \log(p(\mu, \log \sigma | y)) = -\frac{n}{\sigma^2} \quad \text{at } \hat{\theta}: -n \cdot \frac{n}{(n-1)s^2} = \frac{-n^2}{(n-1)s^2}$$

$$\frac{\partial^2}{\partial \mu \partial \log \sigma} \log(p(\mu, \log \sigma | y)) = -2n(\bar{y} - \mu) e^{-2 \log \sigma} = \frac{-2n(\bar{y} - \mu)}{\sigma^2} \quad \text{at } \hat{\theta}: 0$$

$$\frac{\partial^2}{(\partial \log \sigma)^2} \log(p(\mu, \log \sigma | y)) = -2[(n-1)s^2 + n(\bar{y} - \mu)^2] e^{-2 \log \sigma} \quad \text{at } \hat{\theta}: \frac{-2(n-1)s^2}{\sigma^2} = \frac{-2ns^2}{s^2} = -2n$$

$$-\mathcal{I}(\hat{\theta}) = \begin{pmatrix} -\frac{n^2}{(n-1)s^2} & 0 \\ 0 & -2n \end{pmatrix}$$

④ Compute the normal distribution approximation

$$p(\theta | y) \approx N(\hat{\theta}, \mathcal{I}(\hat{\theta})^{-1})$$

$$p(\mu, \log \sigma | y) \approx N \left(\begin{pmatrix} \bar{y} \\ \frac{1}{2} \log \left(\frac{(n-1)s^2}{2} \right) \end{pmatrix}, \begin{pmatrix} \frac{n^2}{(n-1)s^2} & 0 \\ 0 & 2n \end{pmatrix}^{-1} \right)$$

Solution to the example.