

1. CH.1: Introduction

1-1 (a) $p(\mathbf{y}|\theta) = \prod_{i=1}^N p(\mathbf{y}_i|\theta) = \prod_{i=1}^N \theta e^{-\theta y_i} = \theta^N e^{-\theta \sum_i y_i} = \theta^N e^{-\theta N \bar{y}}$.

(b) MLE minimizes $\ln p(\mathbf{y}|\theta) = N \ln \theta - \theta N \bar{y}$.
 $\partial \ln p(\mathbf{y}|\theta) / \partial \theta = N/\theta - N \bar{y} = 0 \Rightarrow 1/\theta = \bar{y} \Rightarrow \hat{\theta} = 1/\bar{y}$.

(c) $p(\theta|\mathbf{y}) \propto p(\boldsymbol{\theta}) \times p(\mathbf{y}|\boldsymbol{\theta}) = [e^{-\theta}] \times \theta^N e^{-\theta N \bar{y}} = \theta^N e^{-\theta(N \bar{y} + 1)}$.

(d) Part (c) is gamma density $f(\theta) \propto \theta^{a-1} e^{-\theta/b}$ with $a = (N + 1)$ and $b = 1/(N \bar{y} + 1)$.

The posterior mean is $E[\theta] = ab = (N + 1) \times [1/(N \bar{y} + 1)] = (N + 1)/(N \bar{y} + 1)$.

1-2 (a) $p(\mathbf{y}|\theta) = \prod_{i=1}^N p(\mathbf{y}_i|\theta) = \prod_{i=1}^N (2\pi)^{-1/2} \exp[-(y_i - \theta)^2/2]$
 $= (2\pi)^{-N/2} \exp[-\sum_i (y_i - \theta)^2/2]$.

So $p(\mathbf{y}|\theta) \propto \exp[-\sum_i (y_i - \theta)^2/2] = \exp\{-\sum_i (y_i - \bar{y})^2/2\} - N(\bar{y} - \theta)^2/2]$
 (given hint.) $= \exp[-\sum_i (y_i - \bar{y})^2/2] \exp[-N(\bar{y} - \theta)^2/2]$

The first term does not involve θ so $p(\mathbf{y}|\theta) \propto \exp[-N(\bar{y} - \theta)^2/2]$

(b) MLE minimizes $\ln p(\mathbf{y}|\theta) \propto \ln\{\exp[-N(\bar{y} - \theta)^2/2]\} = N(\bar{y} - \theta)^2/2$.

$\partial \ln p(\mathbf{y}|\theta) / \partial \theta = -N(\bar{y} - \theta) = 0 \Rightarrow \hat{\theta} = \bar{y}$.

(c) $p(\theta|\mathbf{y}) \propto p(\boldsymbol{\theta}) \times p(\mathbf{y}|\boldsymbol{\theta}) \propto [\exp(-\theta^2/2)] \times \exp[-N(\bar{y} - \theta)^2/2]$
 $= \exp\{-\frac{1}{2}[N(\bar{y} - \theta)^2 + \theta^2]\}$.

(d) $N(\bar{y} - \theta)^2 + \theta^2 = N\bar{y}^2 - 2N\theta\bar{y} + N\theta^2 + \theta^2 = (N + 1)\theta^2 - 2N\theta\bar{y} + N\bar{y}^2$
 $= (N + 1)\{\theta^2 - 2\frac{N}{N+1}\theta\bar{y}\} + N\bar{y}^2 = (N + 1)\{\theta^2 - \frac{N}{N+1}\bar{y}\}^2 - (N + 1)(\frac{N}{N+1}\bar{y})^2 + N\bar{y}^2$.

(e) $p(\theta|\mathbf{y}) \propto \exp\{-\frac{1}{2}[N(\bar{y} - \theta)^2 + \theta^2]\}$
 $\propto \exp\{-\frac{1}{2}[(N + 1)\{\theta - \frac{N}{N+1}\bar{y}\}^2 - (N + 1)(\frac{N}{N+1}\bar{y})^2 + N\bar{y}^2]\}$
 $= \exp\{-\frac{1}{2}[(N + 1)\{\theta - \frac{N}{N+1}\bar{y}\}^2]\} \times \exp\{-\frac{1}{2}[(N + 1)(\frac{N}{N+1}\bar{y})^2 + N\bar{y}^2]\}$
 $\propto \exp\{-\frac{1}{2}[(N + 1)\{\theta - \frac{N}{N+1}\bar{y}\}^2]\} \propto \exp\{-\frac{1}{2 \times [1/(N+1)]}\{\theta - \frac{N}{N+1}\bar{y}\}^2\}$.

This is the kernel of a normal density with mean $\frac{N}{N+1}\bar{y}$ and variance $1/(N + 1)$.

The posterior mean is $\frac{N}{N+1}\bar{y}$.

(f) From preceding the posterior variance is $1/(N + 1)$.

The MLE is \bar{y} which for $y \sim N[0, 1]$ has variance $1/N$ that exceeds $1/(N + 1)$.

Intuitively, using prior information improves precision.

1-3 To do.

This question uses simulated methods to calculate moments, using $\hat{E}[g(\boldsymbol{\theta})] = \frac{1}{S} \sum_{s=1}^S g(\boldsymbol{\theta}^{(s)})$.

Suppose the posterior density for parameter θ is $N[0, 1]$.

- (a) Calculate the posterior mean of θ using $S = 10, 100, 1000$ and $10,000$ draws.
- (b) Calculate the variance of this simulation estimate when $S = 100$ (see Koop).
- (c) Calculate $E[\exp(-\exp(x))]$ using $S = 10, 100, 1000$ and $10,000$ draws.
- (d) Does $E[\exp(-\exp(x))]$ actually exist? [Hint: This is tricky and can be skipped.]