

# Midterm [20 pts]

March 19th, 2025 in class

PUBH 8442: Bayes Decision Theory and Data Analysis

Give your final answers in simplified, closed form wherever possible. However, partial credit will be awarded for incomplete solutions. Good luck!

1. *Support hotline* [11 pts]

Consider incoming calls to a support hotline. The number of calls taken for a given day  $i$ ,  $c_i$ , is Poisson distributed with rate parameter  $\lambda$ :

$$c_i \stackrel{\text{iid}}{\sim} \text{Poisson}(\lambda) \text{ with pmf } P(c | \lambda) = \frac{\lambda^c e^{-\lambda}}{c!}.$$

The length of each call in hours,  $t_{ij}$ , is exponentially distributed with mean  $1/\theta$ :

$$t_{ij} \stackrel{\text{iid}}{\sim} \text{Exp}(\theta) \text{ with density } p(t | \theta) = \theta e^{-t\theta} \text{ for } j = 1, 2, \dots, c_i.$$

- (a) (3 points) The prior for  $\theta$  is Gamma( $\alpha, \beta$ ):  $p(\theta) = (\beta^\alpha / \Gamma(\alpha)) \theta^{\alpha-1} e^{-\beta\theta}$ . What is the posterior distribution for  $\theta$ , given the call times on the first day (with  $c_1$  known),  $p(\theta | t_{11}, \dots, t_{1c_1})$ ?

This can be found using the Exponential-Gamma model, or derived directly:

$$\begin{aligned} p(\theta | t_{11}, \dots, t_{1c_1}) &\propto p(\theta) \prod_{j=1}^{c_1} p(t_{1j} | \theta) \\ &\propto \theta^{\alpha-1} e^{-\beta\theta} \theta^{c_1} e^{-(t_{11} + \dots + t_{1c_1})\theta} \\ &= \theta^{\alpha+c_1-1} e^{-(\beta+t_{11}+\dots+t_{1c_1})\theta} \\ &\propto \text{Gamma} \left( \alpha + c_1, \beta + \sum_{j=1}^{c_1} t_{1j} \right). \end{aligned}$$

- (b) (2 points) After observing 5 calls on the first day, the *posterior* for  $\lambda$  is  $p(\lambda | c_1 = 5) = \text{Gamma}(7, 2)$ . What was the *prior* for  $\lambda$ ,  $p(\lambda)$ ?

By the Poisson-Gamma model  $p(\lambda | c_i) = \text{Gamma}(a + c_i, b + 1)$  if  $p(\lambda) = \text{Gamma}(a, b)$ , and so it follows that  $p(\lambda) = \text{Gamma}(2, 1)$ . This may also be derived analytically:

$$\begin{aligned} \lambda^8 e^{-2\lambda} &\propto p(\lambda | c_1 = 5) \propto p(\lambda) p(c_1 = 5 | \lambda) \propto p(\lambda) \lambda^5 e^{-\lambda} \\ &\rightarrow p(\lambda) \propto \lambda^3 e^{-\lambda} \propto \text{Gamma}(2, 1). \end{aligned}$$

Let  $T_i$  denote the total call time on day  $i$ ,  $T_i = t_{i1} + \dots + t_{ic_i}$ . Let  $\mathbf{y}_i$  denote all data from day  $i$ ,  $\mathbf{y}_i = \{c_i, t_{i1}, \dots, t_{ic_i}\}$ . For parts c-d below, assume that after the first day  $\lambda$  has posterior  $p(\lambda | \mathbf{y}_1) = \text{Gamma}(7, 2)$  and  $\theta$  has independent posterior  $p(\theta | \mathbf{y}_1) = \text{Gamma}(4, 3)$ .

- (c) (3 points) What is the expected value for the length of a single call on day 2, given day 1,  $E(t_{21} | \mathbf{y}_1)$ ?

$$\begin{aligned}
 \int t_{21} p(t_{21} | y_1) dt_{21} &= \int t_{21} \int p(t_{21} | \theta) \cdot p(\theta | y_1) d\theta dt_{21} \\
 &= \int \left[ \int t_{21} p(t_{21} | \theta) dt_{21} \right] \cdot p(\theta | y_1) d\theta \\
 &= \int (1/\theta) p(\theta | y_1) d\theta \\
 &= \frac{3^4}{\Gamma(4)} \int \theta^2 e^{-3\theta} d\theta \\
 &= \frac{3^4}{\Gamma(4)} \frac{\Gamma(3)}{3^3} = 1.
 \end{aligned}$$

- (d) (3 points) What is the expected value for the total call time on day 2, given day 1,  $E(T_2 | \mathbf{y}_1)$ ? (You may use the result  $E(T_2 | \mathbf{y}_1, c_2) = c_2$ .)

$$\begin{aligned}
 \int T_2 p(T_2 | y_1) dT_2 &= \int T_2 \left[ \sum_{c_2} p(T_2 | c_2) p(c_2 | y_1) \right] dT_2 \\
 &= \sum_{c_2} \left[ \int T_2 p(T_2 | c_2) dT_2 \right] P(c_2 | y_1) \\
 &= \sum_{c_2} c_2 P(c_2 | y) \\
 &= \sum_{c_2} c_2 \int P(c_2 | \lambda) p(\lambda | y_1) d\lambda \\
 &= \int \left[ \sum_{c_2} c_2 P(c_2 | \lambda) \right] p(\lambda | y_1) \\
 &= \int \lambda p(\lambda | y_1) = 7/2.
 \end{aligned}$$

2. Bayesian P-Value [3 pts]

Consider  $y_1, \dots, y_n \stackrel{iid}{\sim} N(\theta, \sigma^2)$ , with  $\sigma^2$  known and a flat prior on  $\theta$ :  $p(\theta) = 1 \forall \theta$ . Let  $\mathbf{y} = (y_1, \dots, y_n)$ , and let  $T(\cdot)$  give the sample mean:  $T(\mathbf{y}) = \bar{y}$ . What is the posterior predictive p-value,

$$P(T(\mathbf{Y}) \geq T(\mathbf{y}) | \mathbf{y})?$$

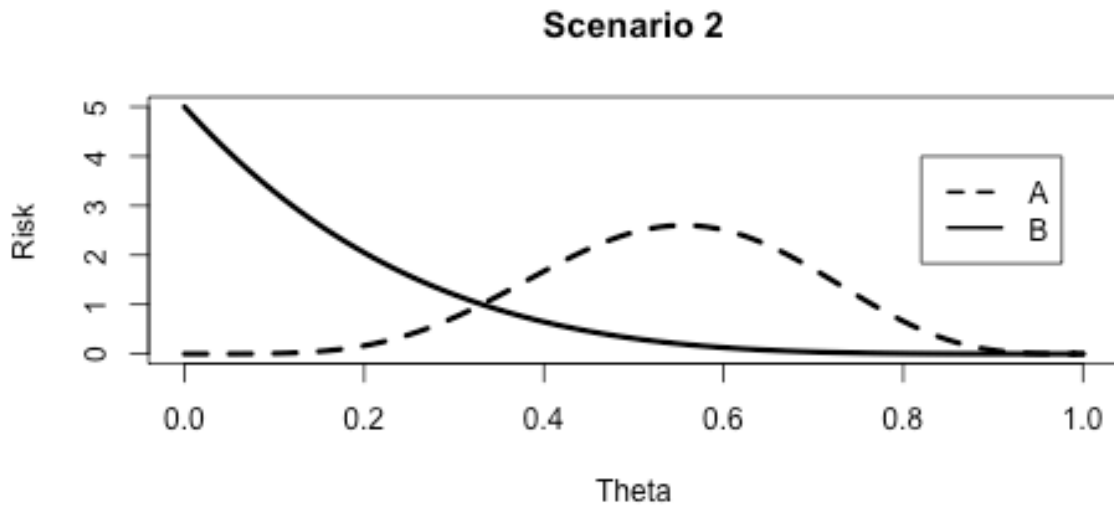
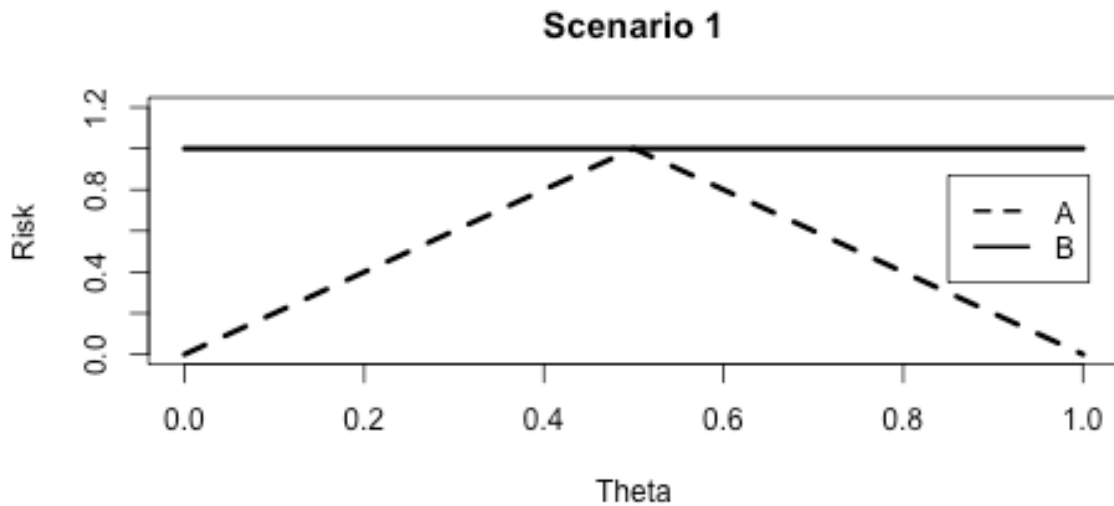
The posterior distribution of  $\theta$  given  $\mathbf{y}$  is

$$\theta | \mathbf{y} \sim N(\bar{y}, \sigma^2/n)$$

(see slide 9 of the “More on Interval Estimation” notes). So, because  $\bar{Y} \sim N(\theta, \sigma^2/n)$ , it follows from the marginal distribution of the normal-normal model that

$$\bar{Y} | \mathbf{y} \sim N(\bar{y}, 2\sigma^2/n).$$

Thus,  $P(\bar{Y} \geq \bar{y} | \mathbf{y}) = \frac{1}{2}$ .



3. *Decision rules* [6 pts]

The above figure shows the frequentist risk of two decision rules ( $A$  and  $B$ ) as a function of an unknown parameter  $\theta$ , under two different scenarios. For each scenario,  $A$  and  $B$  are the only two potential decisions (action space =  $\{A,B\}$ ),  $\theta$  can take any value between 0 and 1, and  $\theta$  has a prior that is positive over the unit interval  $p(\theta) > 0 \forall \theta \in [0, 1]$ .

For each of the following, answer “yes”, “no”, or “not enough informations”:

- (a) Is  $A$  admissible in Scenario 1? *Yes*
- (b) Is  $A$  minimax in Scenario 1? *Yes*
- (c) Is  $A$  a Bayes rule in Scenario 1? *Yes*
- (d) Is  $B$  admissible in Scenario 1? *No*
- (e) Is  $B$  minimax in Scenario 1? *Yes*
- (f) Is  $B$  a Bayes rule in Scenario 1? *No*

- (g) Is  $A$  admissible in Scenario 2? *Yes*
- (h) Is  $A$  minimax in Scenario 2? *Yes*
- (i) Is  $A$  a Bayes rule in Scenario 2? *Not enough information*
- (j) Is  $B$  admissible in Scenario 2? *Yes*
- (k) Is  $B$  minimax in Scenario 2? *No*
- (l) Is  $B$  a Bayes rule in Scenario 2? *Not enough information*