

Problem Set 2

Problem 1 (Galenshore distribution). An unknown quantity Y has a Galenshore(a, θ) distribution if its density is given by

$$p(y|\theta) = \frac{2}{\Gamma(a)} \theta^{2a} y^{2a-1} e^{-\theta^2 y^2}$$

for $y > 0$, $\theta > 0$, and $a > 0$. Assume for now that a is known. For this density,

$$\mathbb{E}[Y|\theta] = \frac{\Gamma(a + 1/2)}{\theta \Gamma(a)}, \quad \mathbb{E}[Y^2|\theta] = \frac{a}{\theta^2}.$$

- Identify a class of conjugate prior densities for θ . Plot a few members of this class of densities.
- Let $Y_1, \dots, Y_n \sim \text{Galenshore}(a, \theta)$ be conditionally i.i.d. Find the posterior distribution of θ given $\mathcal{D} = \{Y_1, \dots, Y_n\}$, using a prior from your conjugate class.
- Write down $p(\theta_a|\mathcal{D})/p(\theta_b|\mathcal{D})$ and simplify. Identify a sufficient statistic.
- Determine $\mathbb{E}[\theta|\mathcal{D}]$.
- Determine the form of the posterior predictive density $p(\tilde{y}|\mathcal{D})$.

Problem 2 (unit information prior). Let $X_1, \dots, X_n \sim p(x|\theta)$ be conditionally i.i.d. For observations $\mathcal{D} = (x_1, \dots, x_n)$, the log likelihood is given by $l(\theta|\mathcal{D}) = \sum \log p(x_i|\theta)$, and we denote by $\hat{\theta}$ the maximum likelihood estimate (MLE). The Fisher information, $J(\theta) = -\partial^2 l(\theta|\mathcal{D})/\partial\theta^2$, describes the precision of the MLE $\hat{\theta}$. For situations in which it is difficult to quantify prior information in terms of a probability distribution, some have suggested that the “prior” distribution be based on the likelihood, for example, by centering the prior distribution around the MLE $\hat{\theta}$. To deal with the fact that the MLE is not really prior information, the curvature of the prior is chosen so that it has only “one n th” as much information as the likelihood, so that $-\partial^2 \log p(\theta)/\partial\theta^2 = J(\theta)/n$. Such a prior is called *unit information prior*, as it has as much information as the average amount of information from a single observation. The unit information prior is not really a prior distribution, as it is computed from the observed data. However, it can be roughly viewed as the prior information of someone with weak but accurate prior information.

- Let $X_1, \dots, X_n \sim \text{Bernoulli}(\theta)$ be conditionally i.i.d. Obtain the MLE $\hat{\theta}$ and $J(\hat{\theta})/n$.
- Find a probability density $p_U(\theta)$ such that $\log p_U(\theta) = l(\theta|\mathcal{D})/n + c$, where c is a constant that does not depend on θ . Compute the information $-\partial^2 \log p(\theta)/\partial\theta^2$ of this density.

- (c) Obtain a probability density for θ that is proportional to $p_U(\theta) \times p(\mathcal{D}|\theta)$. Can this be considered a posterior distribution for θ ?

Problem 3 (Poisson population comparison). Let θ_A and θ_B be the average number of children of men in their 30s with and without bachelor's degrees, respectively. Such data is given in the files `menchild30bach.dat` and `menchild30nobach.dat` which are available on the course website. We'll assume Poisson sampling model for the two groups, with the parameterization $\theta_A = \theta$ and $\theta_B = \theta \times \gamma$. In this parameterization, γ represents the relative rate θ_B/θ_A . Let $\theta \sim \Gamma(a_\theta, b_\theta)$ and let $\gamma \sim \Gamma(a_\gamma, b_\gamma)$.

- (a) Obtain the form of the full conditional distribution of θ given \mathcal{D}_A , \mathcal{D}_B , and γ .
- (b) Obtain the form of the full conditional distribution of γ given \mathcal{D}_A , \mathcal{D}_B , and θ .
- (c) Set $a_\theta = 2$ and $b_\theta = 1$. Let $a_\gamma = b_\gamma \in \{8, 16, 32, 64, 128\}$. For each of these five values, run a Gibbs sampler of at least 5,000 iterations and obtain $\mathbb{E}[\theta_B - \theta_A | \mathcal{D}_A, \mathcal{D}_B]$. Describe the effects of the prior distribution for γ on the results.

Solutions will be discussed in class on September 12.