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Choose one problem

1. Assume $X|\theta$ is exponential $\mathcal{E}(1/\theta)$ with density $f(x|\theta) = \frac{1}{\theta}e^{-x/\theta}$, $x \ge 0$. Let F be the cdf corresponding to f. Assume a prior on θ , $\pi(\theta)$.

Let $m_{\pi}(x) = \int_{\Theta} f(x|\theta) \pi(\theta) d\theta$ be the marginal and $M_{\pi}(x) = \int_{0}^{x} m_{\pi}(t) dt$ be its cumulative distribution function. (a) Show that $\theta = \frac{f(x|\theta)}{1 - F(x|\theta)}$ $1-F(x|\theta)$.

(b) Show that Bayes estimator with respect π is $\hat{\theta} = \frac{m_{\pi}(x)}{1 - M_{\text{tot}}}$ $1-M_\pi(x)$.

[Hint. You will need to use a version of Fubini's theorem (Tonelli theorem) and change order of integration. Tonelli theorem allows for change when integrands are nonnegative.]

(c) Suppose you observe $X_i|\theta_i \sim \mathcal{E}(1/\theta_i), i = 1,\ldots,n+1$. Explain how would you estimate θ_{n+1} in the empirical Bayes fashion, using result (b).

2. Assume $[X|\theta] \sim \mathcal{N}(\theta, 1)$ and $[\theta|\mu, \tau^2] \sim \mathcal{N}(\mu, \tau^2)$.

(a) Find the marginal for X.

(b) What are the moment matching estimators of μ and τ^2 , if the sample $X_i \sim \mathcal{N}(\theta_i, 1)$, $i = 1, \ldots, n$, is available.

[Hint. Find the moments of the marginal and be careful, the estimator of the variance need to be non-negative.]

(c) Propose an empirical Bayes estimator of θ based on the considerations in (b).

(d) What modifications in (b) are needed if you use MLE II estimator of μ and τ^2 .

[Sol. moment matching. Marginal is $\mathcal{N}(\mu, 1 + \tau^2)$. $\hat{\mu} = \bar{X}$ and estimator of $1 + \tau^2$ is s^2 . So $\hat{\tau}^2 =$ $\max\{0, s^2 - 1\}$. For MLE $\hat{\tau}^2 = \max\{0, \frac{n-1}{n} s^2 - 1\}$.

3. If the data $X_i \sim f(x_i|\theta)$ can not be reduced by a sufficient statistics, then so called pseudo-Bayes approach is possible. Let T be an estimator of θ for which distribution $q(t|\theta)$ is known. Instead of finding Bayes rule

$$
\delta_{\pi}(x_1,\ldots,x_n) = \frac{\int_{\Theta} \theta \prod_{i=1}^n f(x_i|\theta) \pi(\theta) d\theta}{\int_{\Theta} \prod_{i=1}^n f(x_i|\theta) \pi(\theta) d\theta}
$$

one finds pseudo-Bayes rule

$$
\delta_{\pi}^*(t) = \frac{\int_{\Theta} t g(t|\theta) \pi(\theta) d\theta}{\int_{\Theta} g(t|\theta) \pi(\theta) d\theta}.
$$

Suppose that you have model

$$
X_i \sim \mathcal{N}(\theta, 1),
$$

$$
\theta \sim \mathcal{N}(\mu, \tau^2).
$$

For n large, the distribution of the sample median $m = \text{Med}(X_1, X_2, \ldots, X_n)$, is approximately $\mathcal{N}(\theta, \frac{\pi}{2n})$. Write down pseudo-Bayes estimator of θ using the median estimator of θ and its normal approximation.

4. Another way to justify Stein shrinkage estimator. Mimic the exercise 2. Suppose that you have model

$$
X \sim \mathcal{MVN}_p(\boldsymbol{\theta}, I),
$$

$$
\boldsymbol{\theta} \sim \mathcal{MVN}(0, \tau^2 I).
$$

- (i) Find marginal distribution.
- (ii) Show, in (i) the MLE of τ^2 is

$$
\hat{\tau}^2 = \begin{cases} \sum_{p} x_i^2, & \sum_{i} x_i^2 > p \\ 0, & \text{else} \end{cases}
$$

(iii) Replacing the MLE in the Bayes estimator

$$
\delta_\pi(\boldsymbol{x}) = \frac{\tau^2 \boldsymbol{x}}{1+\tau^2}
$$

the truncated James-Stein estimator is obtained,

$$
\delta_{\text{\tiny EB}}(\boldsymbol{x}) = \left(1 - \frac{p}{\sum x_i^2}\right)_+ \boldsymbol{x},
$$

where $(x)_+$ = max $\{x, 0\}$ is the positive part of x.