Econ 240A: Problem Set 6
Solutions to Selected Problems from Chapter 6

Chuan Goh

28 February 2001

1.

a.

The likelihood is just the joint density of the observations, i.e.,

$$f(x;\mu) = (2\pi)^{-\frac{n}{2}} \exp\left\{-\frac{1}{2}\sum_{i=1}^{n}(x_i-\mu)^2\right\}.$$

b.

We have $p(\mu|x) \propto f(x;\mu)p(\mu)$, where $p(\mu) = (2\pi\frac{1}{k})^{-\frac{1}{2}}\exp\{-\frac{k\mu^2}{2}\}$. So

$$\begin{aligned}
p(\mu|x) &\propto \exp\left\{-\frac{n}{2}(\mu-\bar{x})^2 - \frac{k}{2}\mu^2\right\} \\
&= \exp\left\{-\frac{1}{2}\left[(n+k)\mu^2 - 2n\bar{x}\mu + \frac{n^2\bar{x}^2}{n+k} - \frac{n^2\bar{x}^2}{n+k} + n\bar{x}^2\right]\right\} \\
&\propto \exp\left\{-\frac{1}{2}\left(\sqrt{n+k}\mu - \frac{\bar{x}n}{\sqrt{n+k}}\right)^2\right\} \\
&= \exp\left\{-\frac{n+k}{2}\left(\mu - \frac{n\bar{x}}{n+k}\right)^2\right\},
\end{aligned}$$

which shows that $\mu|x \sim N(\frac{n\bar{x}}{n+k}, \frac{1}{n+k})$.

c.

The *Bayes risk* $R(T,\mu)$ of an estimate T is its expected posterior loss, i.e., $R(T,\mu) = E_{\mu|x}L(T,\mu)$. Here $L(T,\mu) = (T-\mu)^2$, so

$$R(T,\mu) = T^2(x) - 2T(x)\frac{n\bar{x}}{n+k} + \left[\frac{1}{n+k} + \left(\frac{n\bar{x}}{n+k}\right)^2\right].$$

d.

From part c. it should be fairly clear that the procedure T that minimizes Bayes risk is just the posterior mean of μ, i.e., $T^*(x) = \frac{n\bar{x}}{n+k}$.

2.

a.

$$f(x;\mu) = \lambda^n \exp(-\lambda \sum_{i=1}^{n} x_i)$$

b.

Differentiating $\log f(x;\lambda)$ with respect to λ and setting the derivative to zero we find that the maximum likelihood estimator to be $\hat{\lambda}_{ML} = \frac{n}{\sum_{i=1}^{n} x_i} = \bar{x}^{-1}$.

c.

We have an exponential prior density $\pi(\lambda) = \alpha \exp(-\alpha\lambda)$. Let $t = \sum_{i=1}^{n} x_i$ and $u = \lambda(t+\alpha)$. Note that

$$\begin{aligned} \int_0^\infty \pi(\lambda) f(x;\lambda) d\lambda &= \int_0^\infty \alpha\lambda^n \exp\{-\lambda(t+\alpha)\} d\lambda \\ &= \alpha \int_0^\infty \left(\frac{u}{t+\alpha}\right)^n \cdot \frac{1}{t+\alpha} e^{-u} du \\ &= \frac{\alpha}{(t+\alpha)^{n+1}} \Gamma(n+1) \\ &= \frac{\alpha n!}{(t+\alpha)^{n+1}} \end{aligned}$$

Therefore the posterior density of λ is given by $\pi(\lambda|x) = \frac{1}{n!}\lambda^n (t+\alpha)^{n+1} e^{-\lambda(t+\alpha)}$. The *Bayes estimate* of λ, that is, the estimate that minimizes posterior loss is the posterior mean of λ if we have a quadratic loss function as in Exercise 1 above:

$$\begin{aligned} E[\lambda|x] &= \frac{1}{n!}(t+\alpha)^{n+1} \int_0^\infty \lambda^{n+1} e^{-\lambda(t+\alpha)} d\lambda \\ &= \frac{(t+\alpha)^{n+1}}{n!} \cdot \frac{1}{(t+\alpha)^{n+2}} \int_0^\infty u^{n+1} e^{-u} du \\ &= \frac{\Gamma(n+2)}{n!(t+\alpha)} \\ &= \frac{n+1}{t+\alpha} \end{aligned}$$

d.

We have $W = 2n\lambda\bar{x} = 2\lambda\sum_{i=1}^n x_i$, so the characteristic function of W is given by

$$\begin{aligned} c_W(s) &= E[e^{iWt}] \\ &= \prod_{i=1}^n c_{X_i}(2\lambda s) \\ &= \prod_{i=1}^n \int_0^\infty \lambda \exp\{i2\lambda x_i s - \lambda x_i\} dx_i \\ &= \prod_{i=1}^n (1-2is)^{-1} \\ &= (1-2is)^n \\ &= (1-2is)^{\frac{2n}{2}}, \end{aligned}$$

which is the characteristic function of a χ^2_{2n} random variable.

We have $\hat{\lambda}_{ML} = \frac{2n\lambda}{W}$, which is distributed as $2n\lambda\chi_\nu^{-2}$, where χ_ν^{-2} refers to an inverse chi-square distribution with ν degrees of freedom.[1] The pdf of the MLE of λ is therefore given by

$$p(\hat{\lambda}_{ML}) = \frac{(2n\lambda)^n}{2^n\Gamma(n)} \hat{\lambda}_{ML}^{n-1} \exp\left\{-\frac{1}{2}\cdot\frac{2n\lambda}{\hat{\lambda}_{ML}}\right\}.$$

The derivation of $p(\hat{\lambda}_{ML})$ is left as an exercise.

4.

We have $k_1, \ldots, k_n$ iid Bernoulli(p), so the likelihood function is given by

$$f(k_1, \ldots, k_n) = p^{\sum_{i=1}^n k_i}(1-p)^{n-\sum_{i=1}^n k_i}.$$

Let $K = \sum_{i=1}^n k_i$. K is clearly sufficient for p by the factorization criterion. It is also minimal sufficient.[2] Note that if there exists a function h and a statistic U such that $K = h(U)$ then K cannot contain more information about p than U, which (after a moment's thought) indicates that U is also sufficient for p. (Alternatively, sufficiency can be shown by substituting $h(U)$ for K in the likelihood function for the sample.)

a.

We have $U = (k_1, \ldots, k_n)$. Then $K = \sum_{i=1}^n U_i$, so U is sufficient.

---

[1] Suppose $X \sim \chi^2_\nu$. Then $X^{-1} \sim \chi_\nu^{-2}$.

[2] See handout on sufficiency. The Bernoulli class of distributions can be shown to be a member of the exponential family of distributions.

b.

We have $U = (k_1^2, (k_2 + \cdots + k_n)^2)$. Then $K = \sqrt{U_1} + \sqrt{U_2}$ so U is sufficient.

c.

We have $U = \frac{K}{n}$. Then $K = nU$ so U is sufficient.

d.

We have $U = (\frac{K}{n}, k_2^2 + \cdots + k_n^2)$. Then $K = nU_1$ so U is sufficient.

e.

We have $U = k_1^2 + \cdots + k_n^2$. Here $K = U$ so U is sufficient.

6.

We have an estimator $T(X)$ that has finite variance V_T and is unbiased for θ, so its mean squared error is V_T. Denote a Stein shrinkage estimator by $S_\lambda(X) = (1-\lambda)T(X) + \lambda 17$. Note that in general $S_\lambda(X)$ will be biased for θ. Denote the mean squared error of $S_\lambda(X)$ by $M(\lambda)$:

$$M(\lambda) = (1-\lambda)^2 V_T + \lambda^2 (17-\theta)^2.$$

Its derivative is given by

$$M'(\lambda) = -2(1-\lambda)V_T + 2\lambda(17-\theta)^2.$$

For any value of θ $M'(\lambda) < 0$ whenever $\lambda < \frac{V_T}{(17-\theta)^2 + V_T} \leq 1$. Since $S_0(X) = T(X)$, this shows that for λ strictly between zero and a small number less than or equal to 1 the MSE of $S_\lambda(X)$ will be uniformly smaller than that of $T(X)$. Whether $S_\lambda(X)$ or $T(X)$ is the better estimator naturally depends on the utility function of the investigator for the particular application at hand.