## Math 281A HW3

## October 31, 2017

**Problem 1.** Let  $X_i$  be IID  $N(0, \sigma^2)$ . Find  $i(\sigma^2)$ , and show that the usual unbiased estimator achieves it.

**Solution** . Denote  $\theta = \sigma^2$ . The density for  $X_i$  is

$$f_{\theta}(x) = \frac{1}{\sqrt{2\pi\theta}} \exp\{-\frac{x^2}{2\theta}\}$$

and the second order partial derivative of log density against  $\theta$  is

$$\frac{\partial^2 \log f}{\partial \theta^2} = \frac{1}{2\theta^2} - \frac{x^2}{\theta^3}.$$

Now it is easy to see that

$$i(\theta) = -E(\frac{\partial^2 \log f}{\partial \theta^2}) = -\frac{1}{2\theta^2} + \frac{\theta}{\theta^3} = \frac{1}{2\theta^2} = \frac{1}{2\sigma^4}.$$

The usual estimator here is  $\frac{1}{n}\sigma_i X_i^2$  (Note that it is not sample variance since we already know that the mean is zero. Sample variance applies to the situation when the mean is unknown.). The variance is

$$var(\frac{1}{n}\sigma_{i}X_{i}^{2}) = \frac{1}{n}var(X_{i}^{2}) = \frac{\sigma^{4}}{n}var(Z^{2}) = \frac{2\sigma^{4}}{n} = \frac{1}{ni(\sigma^{2})},$$

where Z is standard normal, and the last equation shows that the estimator reaches the CR bound. Note that a fact that the square of the standard normal is Chi-square(1) is used here, and Chi-square(1) has variance 2.

**Problem 2.** If X is normal with mean zero and standard deviation  $\sigma$ , determine  $i(\sigma)$ .

**Solution**. Directly use the previous problem's solution, we have

$$i(\sigma) = i(\sqrt{\theta}) = i(\theta)(1/2\sqrt{\theta})^{-2} = \frac{1}{2\theta^2} * 4\theta = \frac{2}{\theta} = \frac{2}{\sigma^2}.$$

The formula used here is from the fact that CR bound of  $g(\theta)$  is  $[g'(\theta)]^2/I(\theta)$ , then naturally the corresponding Fisher information for  $g(\theta)$  as a whole, is  $I(\theta)[g'(\theta)]^{-2}$ .

**Problem 3.** Show that if X is from a scale family then  $\log X$  is from a location family.

*Proof.* Rewrite  $X = \theta Z$ , then  $\log X = \log \theta + \log Z$ . Denote F as the CDF of  $\log Z$ , we have

$$F_{\theta}(x) = P(\log X \le x) = P(\log Z \le x - \log \theta) = F(x - \log \theta)$$

Reparametrize  $\log \theta = \phi$  and the result is clear.

**Problem 4.** If X is not identically zero and Y is independent of X, and Y has positive density at 0. Show that  $E(X/Y) = \infty$ .

*Proof.* Clearly, the problem is solved once we show that  $E(1/|Y|) = \infty$ . This is done by realizing that there exists some  $\varepsilon > 0$  such that f(y) > f(0)/2 in  $(0, \varepsilon)$  by continuity. Now

$$E(1/|Y|) \ge \int_0^\infty \frac{1}{y} f(y) dy \ge \int_0^\varepsilon \frac{1}{y} f(y) dy \ge 0.5 \int_0^\varepsilon \frac{1}{y} f(0) dy = \infty.$$

**Problem 5.** If X is distributed as  $Pois(\lambda)$ , show that the Fisher information about  $\sqrt{\lambda}$  is independent of  $\lambda$ .

*Proof.* Use the fact the Fisher information about  $\lambda$  is  $1/\lambda$ , and the formula of Problem 2, we have

$$i(\sqrt{\lambda}) = i(\lambda)(1/2\sqrt{\lambda})^{-2} = 4.$$

**Problem 6.** Y is uniformly distributed as  $U[\theta - 0.5, \theta + 0.5]$ , and  $X = Y + \varepsilon$  where  $\varepsilon$  is  $N(0, \sigma^2)$ . Find out the Fisher information of  $\theta$  contained in X when  $\sigma \to 0$ .

**Solution** . The density function of X can be found by convolution as follows

$$f(x) = \int f_Y(t) f_{\varepsilon}(x - t) dt$$

$$= \int_{\theta - 0.5}^{\theta + 0.5} \frac{1}{\sigma} \phi(\frac{x - t}{\sigma}) dt$$

$$= \Phi(\frac{x - \theta + 0.5}{\sigma}) - \Phi(\frac{x - \theta - 0.5}{\sigma}).$$

By the formula of Fisher information, namely as  $E[(f'(X))^2/f(X)]$ , we have the Fisher information as

$$\frac{1}{\sigma^2} \int \frac{(\phi(\frac{x-\theta+0.5}{\sigma}) - \phi(\frac{x-\theta-0.5}{\sigma}))^2}{\Phi(\frac{x-\theta+0.5}{\sigma}) - \Phi(\frac{x-\theta-0.5}{\sigma})} dx = \frac{1}{\sigma^2} \int \frac{(\phi(\frac{x+0.5}{\sigma}) - \phi(\frac{x-0.5}{\sigma}))^2}{\Phi(\frac{x+0.5}{\sigma}) - \Phi(\frac{x-0.5}{\sigma})} dx$$

Change variable  $s = x/\sigma$ , and we have the above equal to

$$\frac{1}{\sigma} \int \frac{(\phi(s+\frac{1}{2\sigma}) - \phi(s-\frac{1}{2\sigma}))^2}{\Phi(s+\frac{1}{2\sigma}) - \Phi(s-\frac{1}{2\sigma})} ds$$

Take an interval  $(1/2\sigma, \infty)$ , we see that on this interval the denominator is bounded from above by  $0.5-\delta$ , with  $\delta$  small, and the nominator is monotone increasing with  $\sigma$  approaching zero. Therefore the above is bounded from below by

$$\frac{1}{\sigma} \int_{1/2}^{\infty} \frac{(\phi(s + \frac{1}{2}) - \phi(s - \frac{1}{2}))^2}{1/2 - \delta} ds \to \infty$$