## Solutions to Homework #3 Math 6070-1, Spring 2006

## 1. Consider a probability density kernel K of the form

$$K(x) = \frac{1}{2\tau} e^{-|x|/\tau}, \qquad -\infty < x < \infty.$$

Here,  $\tau > 0$  is fixed. Assuming that f is sufficiently smooth, then derive the form of the asymptotically optimal bandwidth  $h_n$  in the same manner as we did in the lectures for the case  $\tau = 1$ . The extra parameter  $\tau$  is often used to refine kernel-density estimates that are based on the doubleexponential family.

**Solution:** We compute  $\beta_K$ ,  $\sigma_K^2$ , and  $||K||_2^2$  and plug.

Note that

$$||K||_2^2 = \frac{1}{4\tau^2} \int_{-\infty}^{\infty} e^{-2|x|/\tau} \, dx = \frac{1}{4\tau}.$$

Next, we have

$$\sigma_K^2 = \frac{1}{2\tau} \int_{-\infty}^{\infty} x^2 e^{-|x|/\tau} \, dx = \tau^2 \int_0^{\infty} x^2 e^{-x} \, dx = \Gamma(3)\tau^2 = 2\tau^2.$$

Finally,

$$\beta_K = \frac{\|K\|_2^{2/5}}{\sigma_K^{4/5}} = \frac{(1/(4\tau))^{1/5}}{(2\tau^2)^{2/5}} = \frac{1}{16^{1/5}\tau}$$

- 2. Construct continuous probability densities  $f_1, f_2, \ldots$  and f such that:
  - (a)  $\lim_{n \to \infty} \int_{-\infty}^{\infty} |f_n(x) f(x)| \, dx = 0; \text{ and }$
  - (b) there exist infinitely-many values of x such that  $f_n(x) \not\rightarrow f(x)$  as  $n \rightarrow \infty$ .

**Solution:** I will do a little more and produce a "fancy" counter-example. Namely, I will construct examples of densities  $f, f_1, f_2, \ldots$  such that: (i)  $\lim_{n\to\infty} \int_{-\infty}^{\infty} |f_n(x) - f(x)| \, dx = 0$ ; and yet (ii) for all rational numbers r,  $\lim_{n\to\infty} |f_n(r) - f(r)| = \infty$ .

Because rationals are countable we can label them. So let  $\mu_1, \mu_2, \ldots$  be an enumeration of all rational numbers. Also, let  $\{\epsilon_n\}_{n=1}^{\infty}$  be a sequence of positive numbers such that: (i)  $1/\epsilon_n^{1/4}$  is a positive integer; and (ii)  $\lim_{n\to\infty} \epsilon_n = 0$ . For example, you can set  $\epsilon_n := n^{-4}$  if you would like. Define for all  $i, n \geq 1$ ,

$$\phi_{i,n}(x) := \frac{1}{\epsilon_n \sqrt{2\pi}} \exp\left(-\frac{(x-\mu_i)^2}{2\epsilon_n^2}\right).$$

Define f to be an arbitrary density such that  $0 \le f(x) < \infty$  for all  $x \in \mathbf{R}$ . And for all  $n \ge 1$  define

$$f_n(x) = \left(1 - \epsilon_n^{1/4}\right) f(x) + \epsilon_n^{1/2} \sum_{i=1}^{1/\epsilon_n^{1/4}} \phi_{i,n}(x).$$

Check that  $f_n(x) \ge 0$  and  $\int_{-\infty}^{\infty} f_n(x) dx = 1$ . So each  $f_n$  is a density function. Moreover, the triangle inequality implies that

$$|f_n(x) - f(x)| \le \epsilon_n^{1/4} f(x) + \epsilon_n^{1/2} \sum_{i=1}^{1/\epsilon_n^{1/4}} \phi_{i,n}(x).$$

Therefore,

$$\int_{-\infty}^{\infty} |f_n(x) - f(x)| \, dx \le 2\epsilon_n^{1/4} \to 0 \quad \text{as } n \to \infty$$

But we can note that for all *i* fixed, if  $n \ge i$  then

$$f_n(\mu_i) \ge \epsilon_n^{1/2} \phi_{i,n}(\mu_i) = \frac{1}{\sqrt{2\pi\epsilon_n}} \to \infty, \text{ as } n \to \infty.$$

3. Prove that if f and g are probability densities, then  $\mathscr{F}(f*g)(t) = (\mathscr{F}f)(t) \times (\mathscr{F}g)(t)$  for all t. Use this to prove that if f is a probability density and  $\phi_{\epsilon}$  is the  $N(0, \epsilon^2)$  density, then  $f*\phi_{\epsilon}$  has an integrable Fourier transform.

Solution: Compute directly to find that

$$\mathscr{F}(f*g)(t) = \int_{-\infty}^{\infty} e^{itx} (f*g)(x) dx$$
  
=  $\int_{-\infty}^{\infty} e^{itx} \left( \int_{-\infty}^{\infty} f(y)g(x-y) dy \right) dx$   
=  $\int_{-\infty}^{\infty} \left( \int_{-\infty}^{\infty} e^{it(x-y)}g(x-y) dx \right) e^{ity} f(y) dy$   
=  $(\mathscr{F}f)(t) \times (\mathscr{F}g)(t).$ 

Recall that  $(\mathscr{F}\phi_{\epsilon})(t) = e^{-t^2\epsilon^2/2}$ . Because  $|(\mathscr{F}f)(t)| \leq 1$ , it follows that  $|\mathscr{F}(f * \phi_{\epsilon})(t)| \leq e^{-t^2\epsilon^2/2}$ , which is integrable. In fact,

$$\int_{-\infty}^{\infty} |\mathscr{F}(f * \phi_{\epsilon})(t)| \, dt \le \int_{-\infty}^{\infty} e^{-t^2 \epsilon^2/2} \, dt = \frac{\sqrt{2\pi}}{\epsilon} < \infty.$$

4. Let  $X_1, X_2, \ldots$  be an i.i.d. sample from a density function f. We assume that f is differentiable in an open neighborhood V of a fixed point x, and  $B := \max_{z \in V} |f'(z)| < \infty$ .

(a) Prove that for all  $\lambda > 0$ ,  $m \ge 1$ , and all  $x \in \mathbf{R}$ ,

$$P\left\{\min_{1\leq j\leq m} |X_j - x| \geq \lambda\right\} = \left[1 - \int_{x-\lambda}^{x+\lambda} f(z) \, dz\right]^m$$

Solution: By independence,

$$\mathbf{P}\left\{\min_{1\leq j\leq m} |X_j - x| \geq \lambda\right\} = \left[\mathbf{P}\left\{|X_1 - x| \geq \lambda\right\}\right]^m.$$

Compute the latter probability to finish.

(b) Prove that for all  $\epsilon > 0$  small enough,

$$\max_{z \in [x-\epsilon, x+\epsilon]} |f(x) - f(z)| \le 2B\epsilon.$$

Use this to estimate  $|\int_{x-\epsilon}^{x+\epsilon} f(z) dz - 2\epsilon f(x)|$ .

**Solution:** Apply Taylor's expansion with remainder to find that  $|f(x) - f(z)| \leq B|x - z|$  whenever  $z \in V$ . This implies the first claim. For the second claim we note that by the triangle inequality,

$$\left|\int_{x-\epsilon}^{x+\epsilon} f(z) \, dz - 2\epsilon f(x)\right| \le \int_{x-\epsilon}^{x+\epsilon} |f(z) - f(x)| \, dx.$$

Apply the first claim to deduce that this is at most  $4B\epsilon^2$ .

(c) Suppose that as  $m \to \infty$ ,  $\lambda_m \to \infty$  and  $\lambda_m^2/m \to 0$ . Then, prove that

$$\lim_{m \to \infty} \frac{-1}{2\lambda_m} \ln \mathbb{P}\left\{\min_{1 \le j \le m} |X_j - x| \ge \frac{\lambda_m}{m}\right\} = f(x).$$

Solution: According to part (a) we can write

$$P\left\{\min_{1\leq j\leq m} |X_j - x| \geq \frac{\lambda_m}{m}\right\} = \left[1 - \int_{x-(\lambda_m/m)}^{x+(\lambda_m/m)} f(z) dz\right]^m.$$

Apply (b) to find that

$$P\left\{\min_{1\leq j\leq m} |X_j - x| \geq \frac{\lambda_m}{m}\right\} = \left[1 - \frac{2\lambda_m}{m}f(x) + \delta_m\right]^m$$

where  $|\delta_m| \leq 4B(\lambda_m/m)^2$ . Now recall that for  $\eta > 0$  small,

$$\ln(1-\eta) = -\eta + \frac{1}{2}\eta^2 - \frac{1}{3}\eta^3 \pm \cdots$$

Thus,

$$\left[1 - \frac{2\lambda_m}{m}f(x) + \delta_m\right]^m = e^{-2\lambda_m f(x) + m\delta_m \pm \cdots}$$

Because  $\lambda_m^2/m \to 0$ , it follows that  $(m\delta_m + \cdots) \to 0$  as  $m \to \infty$ . The assertion follows. (d) Devise an estimator of f(x) based on the previous steps.

**Solution:** Choose and fix an enormous integer  $m \ge 1$ . Our goal is to estimate

$$\theta_m := \frac{-1}{2\lambda_m} \ln \mathbb{P}\left\{\min_{1 \le j \le m} |X_j - x| \ge \frac{\lambda_m}{m}\right\}.$$

Choose and fix a massively large integer  $n \ge 1$ . Simulate *n* copies of  $(X_1, \ldots, X_m)$ . Say  $(X_1^1, \ldots, X_m^1)$  through  $(X_1^n, \ldots, X_m^n)$ . Then by the law of large numbers, as  $n \to \infty$ ,

$$\hat{\theta}_{m,n} := \frac{-1}{2\lambda_m} \ln \left( \frac{1}{n} \sum_{\ell=1}^n \mathbf{I} \left\{ \min_{1 \le j \le m} \left| X_j^\ell - x \right| \ge \frac{\lambda_m}{m} \right\} \right) \xrightarrow{\mathbf{P}} \theta_m.$$