

## Statistics 583, Problem Set 1

Wellner; 3/30/2016

**Reading:** Van der Vaart, *Asymp Statist*, pages 211-212;  
Ferguson, *ACLSST*, Chapter 2, pages 8 - 9 and problems 6 - 8, page 12.  
(See also Tsybakov *INS*, section 2.4, page 83 ff.)

**Due:** Wednesday, April 6, 2016

1. For two probability measures on a measurable space  $(\mathcal{X}, \mathcal{A})$ , let  $H(P, Q)$  and  $V(P, Q)$  be the Hellinger and total variation distances between  $P$  and  $Q$  defined by

$$H^2(P, Q) = \frac{1}{2} \int \{\sqrt{p} - \sqrt{q}\}^2 d\mu \quad \text{and} \quad V(P, Q) = \frac{1}{2} \int |p - q| d\mu$$

respectively. Here  $p = dP/d\mu$  and  $q = dQ/d\mu$  where  $\mu$  is any measure dominating both  $P$  and  $Q$  (e.g.  $\mu = P + Q$ ). [Note that some authors do not include the constant factor  $1/2$  in the definitions of  $H^2(P, Q)$  or  $V(P, Q)$ .]

- (a) Show that  $H^2(P, Q) = 1 - \int \sqrt{pq} d\mu \equiv 1 - \rho(P, Q)$ ; here  $\rho(P, Q) = \int \sqrt{pq} d\mu \leq 1$  is known as the *Hellinger affinity*.
- (b) Show that  $V(P, Q) = 1 - \int (p \wedge q) d\mu \equiv 1 - \eta(P, Q)$ ; here  $p \wedge q \equiv \min\{p, q\}$  and  $\eta(P, Q) = \int (p \wedge q) d\mu \leq 1$  is called the *total variation affinity*.
- (c) Use (a) and (b) and problem 1 to show that  $(1/2)\rho(P, Q)^2 \leq \eta(P, Q) \leq \rho(P, Q)$ .

2. With the same notation as in problem 1 show that

$$H^2(P, Q) \leq V(P, Q) \leq \sqrt{2}H(P, Q) (1 - 2^{-1}H^2(P, Q))^{1/2}.$$

3. Using the notation in problem 1, show that  $V(P, Q) = \sup_{A \in \mathcal{A}} |P(A) - Q(A)|$ . (This justifies the terminology “total variation distance”, and is sometime known as Scheffé’s theorem.)
4. Consider testing the simple hypothesis  $H : X \sim P$  versus the simple alternative  $K : X \sim Q$ . Let  $\phi$  be a test of  $H$  versus  $K$ , and let  $a \equiv E_Q(1 - \phi)$ ,  $b \equiv E_P\phi$ .
  - (a) Find a test  $\phi$  which minimizes  $a + Db$  where  $D > 0$  is a fixed number. Relate the test you find to the Bayes rule for some prior  $\Lambda = (\lambda, 1 - \lambda)$  on  $\{P, Q\}$ .
  - (b) When  $D = 1$ , relate the minimized total  $a + b$  to the Bayes risk and to the total variation distance  $V(P, Q)$  between  $P$  and  $Q$  (or  $\int (p \wedge q) d\mu$  for some dominating measure  $\mu$ , e.g.  $P + Q$ ).

5. (a) Suppose that  $\{p_n\}$  is a sequence of densities with respect to a dominating measure  $\mu$  that satisfies  $p_n(x) \rightarrow p_0(x)$  for all  $x \in \mathcal{X}$  where  $p_0$  is the density corresponding to a probability measure  $P_0$ . Show that  $V(P_n, P_0) \rightarrow 0$ .
- (b) Give two examples of such a sequence  $p_n$ , including one in which the dominating measure  $\mu$  is Lebesgue measure on  $\mathbb{R}$  and one in which the dominating measure is counting measure on the non-negative integers.
6. **Optional bonus problem 1:** Suppose that  $X_1, \dots, X_n$  are i.i.d.  $P$  on  $(\mathcal{X}, \mathcal{A})$ , let let  $\mathbb{P}_n = n^{-1} \sum_{i=1}^n \delta_{X_i}$  denote the empirical measure, and let  $\mathbb{G}_n \equiv \sqrt{n}(\mathbb{P}_n - P)$  be the empirical process. Let  $\mathcal{F}$  be a class of real valued measurable functions from  $\mathcal{X}$  to  $\mathbb{R}$  with  $\mathcal{F} \subset L_2(P)$ , and let  $f_j \in \mathcal{F}$  for  $j = 1, \dots, k$ . Thus  $\mathbb{G}_n(f_j) = \sqrt{n}(\mathbb{P}_n(f_j) - P(f_j))$  for  $j = 1, \dots, k$ . Use the multivariate CLT to show that

$$(\mathbb{G}_n(f_1), \dots, \mathbb{G}_n(f_k)) \rightarrow (\mathbb{G}(f_1), \dots, \mathbb{G}(f_k)) \sim N_k(0, \Sigma_k(f, P))$$

where  $\Sigma_k(f, P)$  is the  $k \times k$  matrix with  $i, j$ th entry given by

$$\text{Cov}(f_i(X_1), f_j(X_1)) = P(f_i f_j) - P(f_i)P(f_j)$$

and  $\mathbb{G}$  denotes a mean zero Gaussian process with the same covariance structure as  $\mathbb{G}_n$ .