#### Stat210B: Theoretical Statistics

Lecture Date: March 07, 2007

Scribe: Wei-Chun Kao

### Asymptotics of Empirical Processes

Lecturer: Michael I. Jordan

1

**Lemma 1.** (van der Vaart, 1998, lemma 19.24) Let  $\mathcal{F}$  be P-donsker, and  $\hat{f}_n$  be a random sequence of functions taking values in  $\mathcal{F}$  s.t.

$$\int (f_n(x) - f_0(x))^2 dP(x) \xrightarrow{P} 0$$

for some  $f_0$  in  $\mathcal{L}_2(P)$ , then we have

$$G_n(\hat{f}_n - f_0) \xrightarrow{P} 0,$$

and

$$G_n \hat{f}_n \xrightarrow{d} G_P f_0$$

with  $G_n = \sqrt{n}(P_n - P)$ .

*Proof.* Sketch: Uses uniform continuity of sample paths of  $G_p$  with CMT.

# 2 An Example: Mean Absolute Deviation

Define mean absolute deviation

$$M_n = \frac{1}{n} \sum_i |X_i - \bar{X}_n|$$

Let F denote the unknown CDF. W.l.o.g, let Fx = 0. Let  $F_n|X - \theta| = \frac{1}{n} \sum_i |X_i - \theta|$ . If  $Fx^2 < \infty$ , and if  $\theta \in \Theta$  for a compact  $\Theta$ , then  $\{|x - \theta|\}$  is F-Donsker (van der Vaart, 1998, example 19.7)

$$F(|x - \bar{X}_n| - |x|)^2 \le |\bar{X}_n|^2 \xrightarrow{P} 0$$

By Lemma 1, we have

$$G_n|x - \bar{X}_n| - G_n|x| \xrightarrow{P} 0 \tag{1}$$

Consider

$$\sqrt{n}(M_n - F|x|) = \sqrt{n}(F|x - \bar{X}_n| - F|x|) + G_n|x| + o_P(1),$$
(2)

assume that  $\theta \mapsto F|x-\theta|$  is differentiable at  $\theta = 0$ , differentiate  $F|x-\theta|$  at  $\theta = 0$  we have the derivative:

2F(0) - 1.

Apply Delta Method on  $\sqrt{n}(F|x - \bar{X}_n| - F|x|)$ , we have

$$\sqrt{n}(F|x - \bar{X}_n| - F|x|) = -(2F(0) - 1)\sqrt{n}((x - \bar{X}_n) - x) + o_P(1)$$
(3)

$$= (2F(0) - 1)\sqrt{n}X_n \tag{4}$$

$$= (2F(0) - 1)\sqrt{n}(F_n - F)x + o_P(1)$$
(5)

$$= (2F(0) - 1)G_n x + o_P(1).$$
(6)

Therefore, we have

$$\sqrt{n}(M_n - F|x|) = ((2F(0) - 1)x + |x|) + o_P(1)$$
(7)

$$\stackrel{d}{\longrightarrow} \quad G_P((2F(0)-1)x+|x|). \tag{8}$$

Thus,  $M_n$  is AN with mean 0 and variance equals to variance of  $(2F(0) - 1)X_1 + |X_1|$ . We lose (2F(0) - 1)X term by not knowing the mean of X. When the mean and median are the same, 2F(0) - 1 = 0, in which case we don't incur any extra variance by having to estimate the location parameter.

## 3 AN of Z-estimators

**Definition 2.** A function  $\psi_{\theta}(x)$  is Lipschitz if  $\exists$  a function  $\dot{\psi}(x)$  s.t.

$$||\psi_{\theta_1}(x) - \psi_{\theta_2}(x)|| \le \dot{\psi}(x)||\theta_1 - \theta_2||$$

 $\forall \theta_1, \theta_2 \text{ in some neighborhood of } \theta_0 \text{ and } P\dot{\psi}^2 \leq \infty.$ 

**Theorem 3.** (van der Vaart, 1998, Theorem 5.21) For each  $\theta_0$  in an open subset of Euclidean space, let  $\psi_{\theta}(x)$  be Lipschitz. Assume  $P||\psi_{\theta_0}||^2 \leq \infty$ ,  $P\psi_{\theta}$  is differentiable at  $\theta_0$  with derivative  $V_{\theta_0}$  (note that it is different from " $\psi_{\theta}$  is differentiable"). Let

$$P_n \psi_{\hat{\theta}_n} = o_P(n^{-1/2}) (a \text{ "near zero"}).$$

$$\tag{9}$$

Assume  $\hat{\theta}_n \xrightarrow{P} \theta_0$  (consistency). Then we have

$$\sqrt{n}(\hat{\theta}_n - \theta_0) = -V_{\theta_0}^{-1} \frac{1}{\sqrt{n}} \sum_i \psi_{\theta_0}(x_i) + o_P(1),$$

and

$$\hat{\theta}_n - \theta_0$$
 is AN with zero mean and covariance  $V_{\theta_0}^{-1}(P\psi_{\theta_0}\psi'_{\theta_0})V_{\theta_0}^{-2}$ 

*Proof.* (van der Vaart, 1998, example 19.7) shows that Lipschitz functions are *P*-Donsker. Apply Lemma 1 we have

$$G_n\psi_{\hat{\theta}_n} - G_n\psi_{\theta_0} \stackrel{P}{\longrightarrow} 0$$

By assumption that  $\sqrt{n}P_n\psi_{\hat{\theta}_n} = o_P(1)$ , we have

$$G_n \psi_{\hat{\theta}_n} = -\sqrt{n} P \psi_{\hat{\theta}_n} + o_P(1) \tag{10}$$

$$= \sqrt{n} P(\psi_{\theta_0} - \psi_{\hat{\theta}_n}) + o_P(1), \tag{11}$$

with  $P\psi_{\theta_0} = 0$  by definition. Apply Delta Method, or (van der Vaart, 1998, Lemma 2.12), we have

$$\sqrt{n}V_{\theta_0}(\theta_0 - \hat{\theta}_n) + \sqrt{n} \ o_P(||\hat{\theta}_n - \theta_0||) = G_n\psi_{\theta_0} + o_P(1).$$
(12)

By invertability of  $V_{\theta_o}$ , we have

$$\left| \sqrt{n} || \hat{\theta}_n - \theta_o || \leq \left| |V_{\theta_0}^{-1}|| \sqrt{n} || V_{\theta_0}(\hat{\theta}_n - \theta_0) || \right|$$

$$\tag{13}$$

$$= O_P(1) + o_P(\sqrt{n}||\hat{\theta}_n - \theta_0||).$$
(14)

Inequality (14) is obtained by plugging (12) into (13) and using triangle inequality. Therefore, we have

$$\hat{\theta}_n \text{ is } \sqrt{n} - \text{consistent.}$$
 (15)

By (12) and (15), we have

$$\sqrt{n}V_{\theta_0}(\hat{\theta}_n - \theta_0) = -G_n\psi_{\theta_0} + o_P(1).$$
(16)

Multiply both side by  $V_{\theta_0}^{-1}$  to get the result.

# References

van der Vaart, A. W. (1998). Asymptotic Statistics. Cambridge University Press, Cambridge.