## Solution to HW2.3

(Hard; extremely optional) In class on September 11 you saw lots of technical details that are usually hidden in a course at this level. In particular, you saw the role played by the process  $Z_n(t) = n^{-1/2} \sum_{i \leq n} \overset{\bullet}{g}(x_i, t)$  for  $t \operatorname{near} \theta$ . Define  $H_{\theta}(t) = \mathbb{E}_{\theta} \overset{\bullet}{g}(z, t)$ and

$$W_n(t) = Z_n(t) - \mathbb{E}_{\theta} Z_n(t) = n^{-1/2} \sum_{i \le n} \left( \overset{\bullet}{g}(x_i, t) - H_{\theta}(t) \right).$$

For each constant C show (under the assumptions described in class) that

$$\mathbb{E}_{\theta} \sup_{|h| \le C} |W_n(\theta + h/\sqrt{n}) - W_n(\theta)| \to 0 \quad \text{as } n \to \infty.$$

What does this tell you about the behavior of  $Z_n(\theta_n^*)$  (under  $\mathbb{P}_{\theta}$ ) if  $\theta_n^*$  is a root-*n* consistent estimator for  $\theta$ ? Hint: Use more Taylor, starting from

$$\sqrt{n} \left( Z_n(\theta + \delta) - Z_n(\theta) \right) = \sum_{i \le n} \delta \int_0^1 \overset{\bullet}{g} (x_i, \theta + s\delta) \, ds.$$

I'll use primes rather than dots to indicate derivatives with respect to the parameter, because  $\overset{\bullet\bullet}{g}(z,t)$  looks weird. Maybe it would be better use another letter, say  $q = \overset{\bullet}{g}$ , because  $\overset{\bullet\bullet}{q}$  looks better than  $\overset{\bullet\bullet\bullet}{g}$ .

## 0.1 Assumptions

The assumptions are

- (i)  $\mathbb{E}_{\theta}|g'(z,\theta)|^2 < \infty$  and  $\mathbb{E}_{\theta}g(z,\theta) = 0$
- (ii)  $\mathbb{E}_{\theta}|g''(z,\theta)| < \infty$
- (iii) There exists a neighborhood  $U = (\theta \epsilon_0, \theta + \epsilon_0)$  of  $\theta$  and a function M for which

 $|g'''(z,t)| \le M(z)$  for all  $t \in U$  and all z.

Also,  $\mathbb{E}_{\theta} M < \infty$ .

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## 0.2 Pointwise control

Taylor's theorem with remainders written in integral form make it easier to control the error terms in the approximations for  $W_n$ . Start with the pointwise approximation to g'. For any fixed  $\delta$  with  $|\delta| \leq \epsilon_0$ ,

$$<1> \qquad g'(z,\theta+\delta) - g'(z,\theta) = \int_0^1 \frac{\partial}{\partial s} g''(z,\theta+s\delta) \, ds = \delta \int_0^1 g''(z,\theta+s\delta) \, ds.$$

Similarly,

$$g''(z,\theta+s\delta) - g''(z,\theta) = \delta \int_0^s g'''(z,\theta+t\delta) dt$$

Combine the last two equalities to deduce that

$$r_{\theta}(z,\delta) := g'(z,\theta+r) - g'(z,\theta) - \delta g''(z,\theta)$$
$$= \delta^2 \iint \{0 < t < s < 1\} g'''(z,\theta+t\delta) \, dt \, ds$$

and

<2> 
$$|r_{\theta}(z,\delta)| \leq \iint \{0 < t < s < 1\} M(z) \, dt \, ds = \frac{1}{2} \delta^2 M(z).$$

## 0.3 Approximations

Temporarily write  $a_n$  for  $n^{-1/2}$ . By definition,

$$H_{\theta}(\theta + \delta) = \mathbb{E}_{\theta}g'(z, \theta + \delta)$$
  
=  $\mathbb{E}_{\theta} \left(g'(z, \theta) + \delta g''(z, \theta) + r_{\theta}(z, \delta)\right)$   
=  $0 - \delta \mathbb{I}(\theta) + R(\delta)$ 

where

$$|R(\delta)| \leq \mathbb{E}_{\theta} |r_{\theta}(z, \delta)| \leq \frac{1}{2} \delta^2 \mathbb{E}_{\theta} M$$
 if  $|\delta| \leq \epsilon_0$ .

In particular, if  $|h| \leq C$  and  $Cn^{-1/2} \leq \epsilon_0$ , then

 $<\!\!3\!\!>$ 

$$\mathbb{E}_{\theta} Z_n(\theta + ha_n) = a_n^{-1} H_{\theta}(\theta + ha_n) = -h\mathbb{I}(\theta) + R(ha_n)$$

where  $|R(ha_n)| \leq Ka_n$  for  $K := C^2 \mathbb{E}_{\theta} M/2$ .

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Similarly,

$$Z_n(\theta + ha_n) = a_n \sum_{i \le n} \left( g'(x_i, \theta) + ha_n g''(x_i, \theta) + r_\theta(x_i, ha_n) \right)$$
$$= Z_n(\theta) + hJ_n + R_n(ha_n)$$

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where  $J_n = n^{-1} \sum_{i \le n} g''(x_i, \theta)$  and

$$|R_n(ha_n)| \le \frac{a_n C^2}{2n} \sum_{i \le n} M(x_i).$$

From  $\langle \mathbf{3} \rangle$  and  $\langle \mathbf{4} \rangle$ , for  $|h| \leq C$ 

$$\Delta_n(C) := \sup_{|h| \le C} |W_n(\theta + ha_n) - W_n(\theta)| \le C|J_n + \mathbb{I}(\theta)| + R_n(ha_n) + Ka_n.$$

In HW2.3 I asked you to show that  $\mathbb{E}_{\theta}\Delta_n(C) \to 0$  for each fixed C, in the mistaken belief that it would make the problem easier. The contributions from  $R_n$  is easily disposed of:

$$|\mathbb{E}_{\theta}R_n(ha_n)| \le a_n C^2 \mathbb{E}_{\theta} M.$$

The SLLN tells us that  $J_n + \mathbb{I}(\theta) \to 0$  with  $\mathbb{P}_{\theta}$ -probability one. You would need to make some sort of uniform integrability argument to deduce that  $\mathbb{E}_{\theta}|J_n + \mathbb{I}(\theta)| \to 0$ . (Sorry about that.)

In fact we only need the weaker convergence in probability,

$$\mathbb{P}_{\theta}\{\Delta_n(C) > \epsilon\} \to 0 \qquad \text{as } n \to \infty, \text{ for each fixed } \epsilon > 0 \text{ and } C < \infty,$$

for which a WLLN applied to  $J_n + \mathbb{I}(\theta)$  suffices.

Let me show you why  $\langle \mathbf{6} \rangle$  suffices to control  $Z_n(\theta_n^*)$  for a root-n consistent estimator  $\theta_n^*$ . Define  $h_n^* = \sqrt{n}(\theta^* - \theta)$ . For each  $\epsilon > 0$  there exists a constant  $C_{\epsilon}$  for which

$$\mathbb{P}_{\theta}\{|h_n^*| > C_{\epsilon}\} < \epsilon \quad \text{for all } n.$$

The equality

$$Z_n(\theta_n^*) - Z_n(\theta) = W_n(\theta_n^*) - W_n(\theta)h_n^*\mathbb{I}(\theta)$$

shows that

$$|Z_n(\theta_n^*) - Z_n(\theta) + h_n^* \mathbb{I}(\theta)| \le \Delta_n(C_{\epsilon}) + Ka_n \quad \text{whenever } |h_n^*| \le C_{\epsilon}.$$

It follows that  $\mathbb{P}_{\theta}\{|Z_n(\theta_n^*) - Z_n(\theta) + h_n^*\mathbb{I}(\theta)| > 2\epsilon\} \to 0$  as  $n \to \infty$ , for each  $\epsilon > 0$ .

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