Stat210B: Theoretical Statistics **Lecture Date: January 25, 2007**

Lecture 4

Lecturer: Michael I. Jordan *Scribe: Mike Higgins*

1 Recap

Define the following:

$$h_c(x_1, \ldots, x_c) = E(h(x_1, \ldots, x_c, X_{c+1}, \ldots, X_r))$$

$$\zeta_c = Var(h_c(X_1, \ldots, X_c))$$

Now consider a U-Statistic:

$$U_n = \frac{1}{\binom{n}{r}} \sum_{\beta} h(X_{\beta_1}, \ldots, X_{\beta_r})$$

where $E(h) = \theta$ and

$$\text{Var}(U_n) = \binom{n}{r}^{-2} \sum_{c=0}^{r} \binom{n}{r}\binom{r}{c}\binom{n-r}{r-c}\zeta_c$$

Note that

$$\text{Var}(U_n) = \frac{r^2\zeta_1}{n} + O(n^{-2})$$

1.1 Rao-Blackwellization

Note that we can write $U_n = E(h(X_1, \ldots, X_r)|X_{(1)}, \ldots, X_{(r)})$. Thus, we have the following inequality:

$$\begin{aligned} E(U_n^2) &= E(Eh(X_1, \ldots, X_r)|X_{(1)}, \ldots, X_{(r)})^2 \\ &\leq E(Eh^2(X_1, \ldots, X_r)|X_{(1)}, \ldots, X_{(r)}) \\ &= h^2 \end{aligned}$$

2 Projections

Define $\mathcal{L}_2(P)$ as the set of functions that are finite when squared, and let T and $\{S : S \in \mathcal{S}\}$ belong to $\mathcal{L}_2(P)$.

Definition 1. $\hat{S} \in \mathcal{S}$ is a **projection** of T on $\mathcal{S}$ if and only if $E((T - \hat{S})S) = 0$ for all $S \in \mathcal{S}$

Corollary 2 (From van der Vaart Chapter 11). $E(T^2) = E(T - \hat{S})^2 + E(\hat{S}^2)$

Now consider a sequence of statistics T_n and spaces $\mathcal{S}_n$ (that contain constant real variables) with projections $\hat{S_n}$.

Theorem 3. If $\frac{\text{Var}(T_n)}{\text{Var}(\hat{S_n})} \to 1$ then

$$\frac{T_n - E(T_n)}{stdev(T_n)} - \frac{\hat{S_n} - E(\hat{S_n})}{stdev(\hat{S_n})} \xrightarrow{P} 0$$

Proof: Let $A_n = \frac{T_n - E(T_n)}{stdev(T_n)} - \frac{\hat{S_n} - E(\hat{S_n})}{stdev(\hat{S_n})}$. Note that $E(A_n) = 0$ and

$$\text{Var}(A_n) = 2 - 2\left(\frac{\text{Cov}(T_n, \hat{S_n})}{stdev(T_n)stdev(\hat{S_n})}\right)$$

Since $(T_n - \hat{S_n}) \perp \hat{S_n}$ ($(T_n - \hat{S_n})$ is orthogonal to $\hat{S_n}$), we have:

$$\begin{aligned} E(T_n\hat{S_n}) = E(\hat{S_n}^2) \quad &\Rightarrow \\ \text{Cov}(T_n, \hat{S_n}) = \text{Var}(\hat{S_n}) \quad &\Rightarrow \\ A_n \xrightarrow{r=2} 0 \quad &\Rightarrow \\ A_n \xrightarrow{P} 0 \quad & \end{aligned}$$

2.1 Conditional Expectations are Projections

$\mathcal{S} \equiv$ linear space of all measurable functions $g(Y)$ of Y. Define $E(X|Y)$ as a measurable function of Y that satisfies $E(X - E(X|Y))g(Y) = 0$. As a consequence, we have the following:

- Setting $g \equiv 1$, then $E(X - E(X|Y)) = 0 \Rightarrow E(X) = E(E(X|Y))$
- $E(f(Y)X|Y) = f(Y)E(X|Y)$ because
  $E[f(Y)X - f(Y)E(X|Y)]g(Y) = E(X - E(X|Y))f(Y)g(Y) = 0$
- $E(E(X|Y,Z)|Y) = E(X|Y)$

2.2 Hájek Projections

Let $X_1, X_2, \ldots, X_n$ be independent, $\mathcal{S} = \{\sum_{i=1}^n g_i(x_i) : g_i \in \mathcal{L}_2(P)\}$. $\mathcal{S}$ is a Hilbert space.

Lemma 3 (11.10 in van der Vaart). *Let T have a finite 2nd moment. Then*

$$\hat{S} = \sum_{i=1}^{n} E(T|X_i) - (n-1)E(T)$$

Proof:

$$E(E(T|X_i)|X_j) = \begin{cases} E[E(T|X_i)] = E(T) & \text{if } i \neq j \\ E(T|X_i) & \text{if } i = j \end{cases}$$

$$E(\hat{S}|X_j) = \sum_{i/j} E(T) - (n-1)E(T) + E(T|X_j) = E(T|X_j)$$

Thus we have that

$$E[(T - \hat{S})g(X_j)] = E[(E(T - \hat{S})|X_j)g(X_j)] = 0.$$

And we conclude $(T - \hat{S}) \perp \mathcal{S}$.

3 Asymptotic Normality of U-Statistics

Assume $E(h^2) < \infty$. Take Hájek projection of $(U_n - \theta)$ onto $\{\sum_{i=1}^n g_i(x_i) : g_i \in \mathcal{L}_2(P)\}$. Define $\hat{U}_n = \widehat{U_n - \theta} = \sum_{i=1}^n E((U - \theta)|X_i)$. We have that

$$E(h(X_{\beta_1}, \ldots, X_{\beta_r}) - \theta | X_i = x) = \begin{cases} h_1(x) & \text{if } i \in \beta \\ 0 & \text{otherwise} \end{cases}$$

Where $h_1(x) = E(h(x_1, X_2, \ldots, X_r) - \theta)$. Now

$$E(U_n - \theta | X_i) = \frac{1}{\binom{n}{r}} \sum_{\beta} E(h(x_{\beta_1}, \ldots, x_{\beta_r} | X_i) - \theta) = \frac{\binom{n-1}{r-1}}{\binom{n}{r}} = \frac{r}{n} h_1(x_i) \Rightarrow$$

$$\hat{U}_n = \frac{r}{n} \sum_{i=1}^n h_1(x_i)$$

Note that $E\hat{U}_n = 0$ and

$$\text{Var}(\hat{U}_n) = \frac{r^2}{n^2} [n[\text{Var}(h(X_1))]] = \frac{r^2}{n} \zeta_1$$

And so we have $\frac{\text{Var}(U_n)}{\text{Var}(\hat{U}_n)} \to 1$. By our previous theorem we have that

$$\frac{U_n - \theta}{(\frac{r^2}{n}\zeta_1 + O(n^{-2}))^{\frac{1}{2}}} - \frac{\hat{U}_n}{(\frac{r^2}{n}\zeta_1)^{\frac{1}{2}}} \xrightarrow{P} 0$$

By Slutsky we have

$$\sqrt{n}(U_n - \theta - \hat{U}_n) \xrightarrow{P} 0$$

By CLT we have

$$\sqrt{n}\hat{U}_n \xrightarrow{d} N(0, r^2\zeta_1)$$

And by Slutsky again we have

$$\sqrt{n}(U_n - \theta) \xrightarrow{d} N(0, r^2\zeta_1)$$