

Notes on the Hájek projection and Hoeffding Decomposition

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1. The Hájek projection

The following treatment is largely from Van der Vaart (1998).

Suppose that X_1, \dots, X_n are independent random vectors, and let \mathcal{S} denote the set of all variables of the form

$$\sum_{i=1}^n g_i(X_i)$$

for arbitrary measurable functions $g_i : \mathbb{R}^d \rightarrow \mathbb{R}$ with $Eg_i^2(X_i) < \infty$ for $i \in \{1, \dots, n\}$.

Lemma 1. The projection of an arbitrary random variable $T = T(X_1, \dots, X_n)$ with finite second moment onto \mathcal{S} is given by

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

\hat{S} is called the *Hájek projection* of T onto \mathcal{S} .

Proof. Note that $\hat{S} \in \mathcal{S}$. Thus it suffices to show that

$$E\{(T - \hat{S})S\} = 0 \quad \text{for all } S \in \mathcal{S}.$$

But

$$\begin{aligned} E\{(T - \hat{S})S\} &= E\{(T - \hat{S}) \sum_{i=1}^n g_i(X_i)\} \\ &= \sum_{i=1}^n E\{(T - \hat{S})g_i(X_i)\} \\ &= \sum_{i=1}^n EE\{T - \hat{S} | X_i\} g_i(X_i) \end{aligned}$$

$$\begin{aligned}
&= \sum_{i=1}^n E\{g_i(X_i)E[T - \hat{S}]|X_i\} \\
&= \sum_{i=1}^n E\{g_i(X_i) \left(E[T|X_i] - E[\hat{S}|X_i] \right)\}
\end{aligned}$$

where

$$\begin{aligned}
E(\hat{S}|X_i) &= \sum_{j=1}^n E\{E[T|X_j]|X_i\} - (n-1)E(T) \\
&= (n-1)E(T) + E(T|X_i) - (n-1)E(T) \\
&= E(T|X_i).
\end{aligned}$$

for each $i \in \{1, \dots, n\}$. Thus $E[(T - \hat{S})S] = 0$ for each $S \in \mathcal{S}$. □

Note that if X_1, \dots, X_n are also identically distributed and $T(\underline{X}) \equiv T(X_1, \dots, X_n)$ is permutation symmetric (so that $T(\pi\underline{X}) = T(\underline{X})$ for all $\pi \in \Pi_n$), then

$$\begin{aligned}
E(T|X_i = x) &= E(T|X_1 = x) \quad \text{for all } i \in \{1, \dots, n\}, \\
&= ET(x, X_2, \dots, X_n)
\end{aligned}$$

which does not depend on i . It follows that in this case \hat{S} is also the projection of T onto the smaller set \mathcal{S}_0 consisting of all variables of the form $\sum_{i=1}^n g(X_i)$ for an arbitrary measurable function g .

Now suppose that $\{T_n\}$ is a sequence of statistics T_n ((think of $T_n = T(\mathbb{P}_n)$ or $T_n = T_n(X_1, \dots, X_n)$) based on independent X_i 's), and suppose that \mathcal{S}_n is a sequence of linear spaces. Let \hat{S}_n denote the (L_2-) projection of T_n onto \mathcal{S}_n .

Theorem 1. If the linear spaces \mathcal{S}_n contain constants and $Var(T_n)/Var(\hat{S}_n) \rightarrow 1$, then

$$R_n \equiv \frac{T_n - E(T_n)}{\sqrt{Var(T_n)}} - \frac{\hat{S}_n - E(\hat{S}_n)}{\sqrt{Var(\hat{S}_n)}} \rightarrow_p 0.$$

Proof. Now $E(R_n) = 0$ and

$$\begin{aligned}
Cov(T_n, \hat{S}_n) &= E(T_n \hat{S}_n) - E(T_n)E(\hat{S}_n) \\
&= E\hat{S}_n^2 - \{E(\hat{S}_n)\}^2 = Var(\hat{S}_n)
\end{aligned}$$

since both

$$E[(T_n - \hat{S}_n)\hat{S}_n] = 0 \quad \text{and} \quad E[(T_n - \hat{S}_n)1] = 0.$$

Therefore

$$\begin{aligned}
\text{Var}(R_n) &= 2 - 2 \frac{\text{Cov}(T_n, \hat{S}_n)}{\sqrt{\text{Var}(T_n) \cdot \text{Var}(\hat{S}_n)}} \\
&= 2 \left(1 - \frac{\text{Var}(\hat{S}_n)}{\sqrt{\text{Var}(T_n) \cdot \text{Var}(\hat{S}_n)}} \right) \\
&= 2 \left(1 - \sqrt{\frac{\text{Var}(\hat{S}_n)}{\text{Var}(T_n)}} \right) \\
&\rightarrow 0.
\end{aligned}$$

The claimed result follows by Chebychev's (or Markov's) inequality. \square

2. U - statistics and Hájek's projection

Now suppose that X_1, \dots, X_n are i.i.d. random vectors with distribution P on $(\mathbb{R}^d, \mathcal{B}_d) = (\mathcal{X}, \mathcal{A})$ with $n \geq r$. Suppose that $h : \mathcal{X}^r \rightarrow \mathbb{R}$ is measurable and permutation symmetric: $h(\pi \underline{x}) = h(\underline{x})$ for all $\pi \in \Pi_r$. Consider the

$$\theta \equiv T(P) = E_P h(X_1, \dots, X_r).$$

Thus $h(X_1, \dots, X_r)$ is an unbiased estimator of θ . Since n observations (with $n \geq r$ are available, this simple estimator can be improved: by Rao-Blackwell, the new unbiased estimator formed by computing the conditional expectation given a sufficient statistic has smaller variance. Here, for X_i 's with values in \mathbb{R} , the vector of order statistics $X_{(1)}, \dots, X_{(n)}$ is sufficient; and for i.i.d. X_i 's more generally, the empirical measure \mathbb{P}_n is sufficient (see e.g. Dudley (2002), Theorem 1.5.9, page 177):

$$\begin{aligned}
U_n &= \begin{cases} E(h(X_1, \dots, X_r) | X_{(1)}, \dots, X_{(n)}), & \text{if } \mathcal{X} = \mathbb{R}, \\ E(h(X_1, \dots, X_r) | \mathbb{P}_n), & \text{in general.} \end{cases} \\
&= \frac{1}{\binom{n}{r}} \sum_c h(X_{i_1}, \dots, X_{i_r})
\end{aligned}$$

where (i_1, \dots, i_r) denotes one of the $\binom{n}{r}$ collections of r distinct integers between 1 and n .

Now the Hájek projection of U_n is $\hat{S}_n = \hat{U}_n$ given by

$$\hat{U}_n = \sum_{i=1}^n E(U_n - \theta | X_i) = \frac{r}{n} \sum_{i=1}^n h_1(X_i)$$

where

$$h_1(x) = E h(x, X_2, \dots, X_r) - \theta.$$

Theorem 2. If $Eh^2(X_1, \dots, X_r) < \infty$ and $\zeta_1 \equiv \text{Var}(h_1(X_1)) > 0$, then

$$\sqrt{n}(U_n - \theta - \hat{U}_n) \rightarrow_p 0.$$

Hence

$$\begin{aligned} \sqrt{n}(U_n - \theta) &= \sqrt{n}\hat{U}_n + o_p(1) = \frac{r}{\sqrt{n}} \sum_{i=1}^n h_1(X_i) + o_p(1) \\ &\rightarrow_d N(0, r^2 \text{Var}(h_1(X_1))) \end{aligned}$$

where

$$\zeta_1 = \text{Var}(h_1(X_1)) = \text{Cov}(h(X_1, X_2, \dots, X_r), h(X_1, X_2', \dots, X_r')).$$

Proof. The first job is to prove that the form of the Hájek projection \hat{U}_n is as claimed. Since the X_i 's are independent and h is permutation symmetric

$$E \left(h(X_{i_1}, \dots, X_{i_r}) - \theta \middle| X_i = x \right) = \begin{cases} h_1(x), & \text{if } i \in \{i_1, \dots, i_r\}, \\ 0, & \text{if } i \notin \{i_1, \dots, i_r\}. \end{cases}$$

Then we compute

$$\begin{aligned} E(U_n - \theta | X_i) &= \frac{1}{\binom{n}{r}} \sum_c h_1(X_i) 1_{\{i_1, \dots, i_r\}}(i) \\ &= \frac{\binom{n-1}{r-1}}{\binom{n}{r}} h_1(X_i) = \frac{r}{n} h_1(X_i). \end{aligned}$$

Summing these over i gives the claimed result.

To apply Theorem 1 we need to show that

$$\frac{\text{Var}(\hat{U}_n)}{\text{Var}(U_n)} \rightarrow 1. \tag{2.1}$$

Calculation of $\text{Var}(\hat{U}_n)$ is easy:

$$\text{Var}(\hat{U}_n) = \frac{r^2}{n^2} \sum_{i=1}^n \text{Var}(h_1(X_i)) = \frac{r^2}{n} \zeta_1. \tag{2.2}$$

Since the random variables $Y_i \equiv h_1(X_i)$ are i.i.d. with mean zero and finite variance, $\sqrt{n}\hat{U}_n \rightarrow_d N(0, r^2\zeta_1)$ by the (ordinary) CLT.

Calculation of $\text{Var}(U_n)$ is a bit more involved, but not too bad. Let k be the number of indices in common between $\{i_1, \dots, i_r\}$ and $\{i'_1, \dots, i'_r\}$. Then, since there are $\binom{n}{r}$ ways of choosing

$\{i_1, \dots, i_r\}$, $\binom{r}{k}$ ways of choosing k common indices from the choice of $\{i_1, \dots, i_r\}$, and then $\binom{n-r}{r-k}$ ways of choosing the rest of the second block $\{i'_1, \dots, i'_r\}$, we find that

$$\begin{aligned}
\text{Var}(U_n) &= \frac{1}{\binom{n}{r}^2} \sum_c \sum_{c'} \text{Cov}(h(X_{i_1}, \dots, X_{i_r}), h(X_{i'_1}, \dots, X_{i'_r})) \\
&= \frac{1}{\binom{n}{r}^2} \sum_{k=1}^r \binom{n}{r} \binom{r}{k} \binom{n-r}{r-k} \zeta_k \\
&= \sum_{k=1}^r \frac{\binom{r}{k} \binom{n-r}{r-k}}{\binom{n}{r}} \cdot \zeta_k \\
&= E\zeta_K
\end{aligned} \tag{2.3}$$

where $\zeta_0 \equiv 0$ and for $k \in \{1, \dots, r\}$,

$$\zeta_k = \text{Cov}(h(X_1, \dots, X_k, X_{k+1}, \dots, X_r), h(X_1, \dots, X_k, X'_{k+1}, \dots, X'_r)),$$

and where $K \sim \text{Hypergeometric}(n, r)$ (sampling without replacement from an urn containing n balls, r of which are red and $n - r$ of which are blue): i.e.

$$P(K = k) = \frac{\binom{r}{k} \binom{n-r}{r-k}}{\binom{n}{r}} \quad \text{for } k \in \{1, \dots, r\}.$$

The expression in (2.3) can be rewritten as

$$\begin{aligned}
\sum_{k=1}^r \frac{\binom{r}{k} \binom{n-r}{r-k}}{\binom{n}{r}} \cdot \zeta_k &= \sum_{k=1}^r \frac{(r!)^2}{k!(r-k)!^2} \frac{(n-r) \cdots (n-2r+k+1)}{n(n-1) \cdots (n-r+1)} \cdot \zeta_k \\
&\sim r^2 \zeta_1 \cdot \frac{1}{n} \quad \text{if } \zeta_1 > 0.
\end{aligned}$$

Putting this together with (2.2) yields (2.1) and completes the proof. \square

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