

理论证明

定理 2.1 证明：用 Z_i 表示第 i 个单元的被抽中的次数，则有

$$E(Z_i) = np_i, \quad V(Z_i) = np_i(1-p_i), \quad i=1,2,\dots,N$$

和

$$\text{Cov}(Z_i, Z_j) = -np_i p_j, \quad i, j=1,2,\dots,N, \quad i \neq j$$

计算 IHH 估计的偏差为

$$B(\hat{t}_y^*) = E\left(\sum_U \frac{Z_i y_i}{np_i^*} - \sum_U y_i\right) = \sum_U \left(\frac{E(Z_i)}{np_i^*} - 1\right) y_i = \sum_{U_2} \left(\frac{p_i}{p_i^*} - 1\right) y_i$$

方差为

$$\begin{aligned} V(\hat{t}_y^*) &= \sum_U \frac{y_i^2 V(Z_i)}{n^2 p_i^{*2}} + \sum_{i \neq j} \sum_U \frac{y_i y_j \text{Cov}(Z_i, Z_j)}{n^2 p_i^* p_j^*} \\ &= \sum_U \frac{p_i(1-p_i)y_i^2}{np_i^{*2}} - \sum_{i \neq j} \sum_U \frac{p_i p_j y_i y_j}{np_i^* p_j^*} \\ &= \frac{1}{n} \left[\sum_U \frac{p_i y_i^2}{p_i^{*2}} - \left(\sum_U \frac{p_i y_i}{p_i^*} \right)^2 \right] \end{aligned}$$

因此，IHH 估计的均方误差为

$$\begin{aligned} \text{MSE}(\hat{t}_y^*) &= B^2(\hat{t}_y^*) + V(\hat{t}_y^*) \\ &= \left[\sum_{U_2} \left(\frac{p_i}{p_i^*} - 1 \right) y_i \right]^2 + \frac{1}{n} \sum_U \frac{p_i y_i^2}{p_i^{*2}} - \frac{1}{n} \left(\sum_U \frac{p_i y_i}{p_i^*} \right)^2 \\ &= \sum_U \frac{n(p_i - p_i^*)^2 + p_i(1-p_i)}{np_i^{*2}} y_i^2 + \sum_{i \neq j} \sum_U \frac{n(p_i - p_i^*)(p_j - p_j^*) - p_i p_j}{np_i^* p_j^*} y_i y_j \end{aligned}$$

又因为 $E(Z_i Z_j) = \text{Cov}(Z_i, Z_j) + E(Z_i)E(Z_j) = n(n-1)p_i p_j$ ，所以 IHH 估计量均方误差的一个无偏估计为

$$\widehat{\text{MSE}}(\hat{t}_y^*) = \sum_s \frac{n(p_i - p_i^*)^2 + p_i(1-p_i)}{n^2 p_i p_i^*} y_i^2 + \sum_{i \neq j} \sum_s \frac{n(p_i - p_i^*)(p_j - p_j^*) - p_i p_j}{n^2 (n-1) p_i p_j p_i^* p_j^*} y_i y_j$$

证毕。

定理 2.2 证明：根据条件 $\max_{i \in U} |y_i| < \lambda$ 和 $\lambda_1, \min_{i \in U} \{np_i\} < \max_{i \in U} \{np_i\} \leq \lambda_2$ ，有

$$\left| B(\hat{t}_y^*) \right| = \left| \frac{1}{N} \sum_{U_2} \left(\frac{p_i}{p_i^*} - 1 \right) y_i \right| \leq \frac{1}{N} \sum_{U_2} \left| \frac{np_i - np_i^*}{np_i^*} y_i \right| = O\left(\frac{K}{N}\right)$$

又由于 $p_{(K)} \leq (nK+1)^{-1}$ ，所以 K 有界，因此 $B^2(N^{-1}\hat{t}_y^*) = O(n^{-2})$ 。类似地，对于 IHH 的

方差有

$$\begin{aligned}
 \left| V(\hat{t}_y^*) \right| &= \left| \frac{1}{N^2 n} \left[\sum_U \frac{p_i y_i^2}{p_i^{*2}} - \left(\sum_U \frac{p_i y_i}{p_i^*} \right)^2 \right] \right| \\
 &\leq \left| \frac{1}{N^2} \sum_U \frac{np_i y_i^2}{n^2 p_i^{*2}} \right| + \left| \frac{1}{N^2 n} \left(\sum_U \frac{np_i y_i}{np_i^*} \right)^2 \right| \\
 &= O(n^{-1}) + O(n^{-2}) \\
 &= O(n^{-1})
 \end{aligned}$$

证毕。

定理 2.3 证明：注意到，HH 估计的均方误差（方差）为

$$MSE(\hat{t}_y) = \frac{1}{n} \sum_U p_i \left(\frac{y_i}{p_i} - t \right)^2 = \frac{1}{n} \sum_U \frac{y_i^2}{p_i} - \frac{1}{n} \left(\sum_U y_i \right)^2$$

IHH 估计的均方误差为

$$MSE(\hat{t}_y^*) = \left[\sum_{U_2} \left(\frac{p_i}{p_i^*} - 1 \right) y_i \right]^2 + \frac{1}{n} \sum_U \frac{p_i y_i^2}{p_i^{*2}} - \frac{1}{n} \left(\sum_U \frac{p_i y_i}{p_i^*} \right)^2$$

两个均方误差作差得到

$$\begin{aligned}
 MSE(\hat{t}_y) - MSE(\hat{t}_y^*) &= \frac{1}{n} \sum_U \frac{y_i^2}{p_i} - \frac{1}{n} \sum_U \frac{p_i y_i^2}{p_i^{*2}} - \left[\sum_{U_2} \left(\frac{p_i}{p_i^*} - 1 \right) y_i \right]^2 \\
 &\quad + \frac{1}{n} \left(\sum_U \frac{p_i y_i}{p_i^*} \right)^2 - \frac{1}{n} \left(\sum_U y_i \right)^2 \\
 &= \sum_U \frac{y_i^2}{np_i} - \sum_U \frac{p_i y_i^2}{np_i^{*2}} - \left[\sum_{U_2} \left(\frac{p_i}{p_i^*} - 1 \right) y_i \right]^2 \\
 &\quad + \sum_U \frac{p_i^2 y_i^2}{np_i^{*2}} + \sum_{i \neq j} \sum_U \frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \sum_U \frac{y_i^2}{n} - \sum_{i \neq j} \sum_U \frac{y_i y_j}{n} \\
 &= \sum_{U_2} \frac{(p_i^{*2} - p_i^2)(1 - p_i)}{np_i p_i^{*2}} y_i^2 - \left[\sum_{U_2} \left(\frac{p_i}{p_i^*} - 1 \right) y_i \right]^2 \\
 &\quad + \sum_{i \neq j} \sum_U \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right)
 \end{aligned}$$

根据柯西不等式，有

$$\begin{aligned}
& \text{MSE}(\hat{t}_y) - \text{MSE}(\hat{t}_y^*) \dots \sum_{U_2} \frac{(p_i^{*2} - p_i^2)(1 - p_i)}{np_i p_i^{*2}} y_i^2 - K \cdot \sum_{U_2} \frac{(p_i - p_i^*)^2}{p_i^{*2}} y_i^2 \\
& \quad + \sum_{i \neq j} \sum_U \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) \\
& = \sum_{U_2} \frac{(p_i^* - p_i) \left[(1 - p_i - nKp_i) p_i^* + (p_i - p_i^2 + nKp_i^2) \right]}{np_i p_i^{*2}} y_i^2 \\
& \quad + \sum_{i \neq j} \sum_U \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) \\
& \triangleq A_1 + A_2
\end{aligned}$$

其中, K 为 U_2 中的单元个数。显然, 当 $p_{(K)} \gg (nK+1)^{-1}$ 时, $1 - p_i - nKp_i \dots 0, i \in U_2$ 。此时, 上式中 $A_1 \dots 0$ 恒成立。特别地, 当 U_2 中单元的入样概率均相等时, 等号成立。

为完成整个定理的证明, 只需要证明 $A_2 = o(N^2 n^{-1})$ 即可。注意到,

$$\begin{aligned}
A_2 &= \sum_{i \neq j} \sum_U \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) \\
&= \sum_{i \neq j} \sum_{U_2} \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) + \sum_{i \in U_1} \sum_{j \in U_2} \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) \\
& \quad + \sum_{i \in U_2} \sum_{j \in U_1} \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) \\
&= B_1 + B_2 + B_3
\end{aligned}$$

根据条件 $\max_{i \in U} |y_i| < \lambda$ 和 $\lambda_1 \gg \min_{i \in U} \{np_i\} < \max_{i \in U} \{np_i\} \gg \lambda_2$, 有

$$\begin{aligned}
|B_1| &= \left| \sum_{i \neq j} \sum_{U_2} \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) \right| \\
&= \left| \sum_{i \neq j} \sum_{U_2} \left(\frac{np_i np_j - np_i^* np_j^*}{np_i^* np_j^*} y_i y_j \right) \right| \\
&= O(K^2 n^{-1})
\end{aligned}$$

和

$$\begin{aligned}
|B_2| &= \left| \sum_{i \in U_1} \sum_{j \in U_2} \left(\frac{p_i y_i p_j y_j}{np_i^* p_j^*} - \frac{y_i y_j}{n} \right) \right| \\
&= \left| \frac{1}{n} \sum_{i \in U_1} \sum_{j \in U_2} \left(\frac{np_i np_j - np_i^* np_j^*}{np_i^* np_j^*} y_i y_j \right) \right| \\
&= O(NKn^{-1})
\end{aligned}$$

类似于 $|B_2|$, 可以直接得到 $|B_3| = O(NKn^{-1})$ 。因为 $p_{(K)} \gg (nK+1)^{-1}$, 所以 $K = O(1)$ 。

因此, $|B_1|$ 、 $|B_2|$ 和 $|B_3|$ 的阶均为 $o(N^2 n^{-1})$, 故 $A_2 = o(N^2 n^{-1})$ 。证毕。

定理 2.4 的证明: 注意到,

$$\hat{t}_y^* = \frac{1}{n} \sum_s \frac{y_i}{Np_i^*} \triangleq \frac{1}{n} \sum_s \eta_i$$

* MERGEFORMAT (1)

由于每次抽样都是独立进行的，因此 $\{\eta_i\}_{i \in s}$ 是相互独立的。根据定理 2.1 和定理 2.2 知

$$\sum_s E(n^{-1/2} \eta_i) = \sqrt{n} \cdot E(\hat{t}_y^*) = \bar{t}_y + O(n^{-1}) \quad \backslash * \text{ MERGEFORMAT (2)}$$

且

$$\Sigma \triangleq \sum_s V(n^{-1/2} \eta_i) = n \cdot V(N^{-1} \hat{t}_y^*) = \frac{1}{N^2} \left[\sum_U \frac{p_i y_i^2}{p_i^{*2}} - \left(\sum_U \frac{p_i y_i}{p_i^*} \right)^2 \right] = O(1) \quad \backslash * \text{ MERGEFORMAT (3)}$$

此外，对任意的 $\varepsilon > 0$ ，都存在 $\delta > 0$ ，使得

$$\begin{aligned} \sum_s E \left[\left| n^{-1/2} \eta_i \right|^2 I(|\eta_i| > n^{1/2} \varepsilon) \right] &\leq \sum_s E \left[\frac{|n^{-1/2} \eta_i|^{2+\delta}}{\varepsilon^\delta} I(|\eta_i| > n^{1/2} \varepsilon) \right] \\ &\leq \sum_s E \left(\frac{|n^{-1/2} \eta_i|^{2+\delta}}{\varepsilon^\delta} \right) \\ &= \frac{1}{n^{1+\delta/2} \varepsilon^\delta} E \left(\sum_s |\eta_i|^{2+\delta} \right) \\ &= \frac{1}{n^{1+\delta/2} \varepsilon^\delta} \sum_U (np_i |\eta_i|^{2+\delta}) \\ &= \frac{n^{1+\delta}}{N^{1+\delta} n^{\delta/2} \varepsilon^\delta} \cdot \frac{1}{N} \sum_U \left(np_i \left| \frac{y_i}{np_i^*} \right|^{2+\delta} \right) \\ &= o(1) \end{aligned}$$

最后一个等号是根据条件 $\max_{i \in U} |y_i| < \lambda$ 和 $\lambda_1, \min_{i \in U} \{np_i\} < \max_{i \in U} \{np_i\}, \lambda_2$ 获得的。因此，

根据 Lindeberg-Feller 中心极限定理（见文献 Vaart (1998) 中命题 2.27）有

$$\sum_s \left[n^{-1/2} \eta_i - E(n^{-1/2} \eta_i) \right] \xrightarrow{d} N(0, \Sigma)$$

进一步，结合式 (1) ~ (3) 整理以上分布得到 $\sqrt{n} \cdot (\hat{t}_y^* - \bar{t}_y) \xrightarrow{d} N(0, \Sigma)$ 。证毕。

定理 3.1 证明：注意到，

$$\begin{aligned} \text{MSE}(\hat{t}_{sy}^*) &= E(\hat{t}_{sy}^* - t)^2 \\ &= E \left[\sum_{h=1}^L (\hat{t}_h^* - t_h) \right]^2 \\ &= \sum_{h=1}^L \text{MSE}(\hat{t}_h^*) + \sum_{h \neq l}^L \sum_{l=1}^L E[(\hat{t}_h^* - t_h)(\hat{t}_l^* - t_l)] \end{aligned}$$

由于层之间的抽样是独立进行的，因而根据定理 2.2，有

$$\frac{1}{N_h N_l} E[(\hat{t}_h^* - t_h)(\hat{t}_l^* - t_l)] = \frac{1}{N_h N_l} E(\hat{t}_h^* - t_h) E(\hat{t}_l^* - t_l) = O\left(\frac{1}{n_h n_l}\right)$$

因此，根据条件 $n_h/n \rightarrow \lambda_h$ 可知

$$\text{MSE}(\hat{t}_{sy}^*) = \sum_{h=1}^L \text{MSE}(\hat{t}_h^*) + o(N^2 n^{-1})$$

进一步，可推出均方误差的渐近无偏估计为

$$\widehat{\text{MSE}}(\hat{t}_{sy}^*) = \sum_{h=1}^L \widehat{\text{MSE}}(\hat{t}_h^*) + o(N^2 n^{-1})$$

其中， $\widehat{\text{MSE}}(\hat{t}_h^*)$ 表示第 h 层 IHH 估计的无偏均方误差估计。证毕。

定理 3.2 证明： 根据定理 2.3，有

$$\sum_{h=1}^L \text{MSE}(\hat{t}_h^*), \sum_{h=1}^L \text{MSE}(\hat{t}_h^*) + o(n^{-1})$$

再结合式 (4) ~ (5)，得到

$$\text{MSE}(\hat{t}_{sy}^*), \text{MSE}(\hat{t}_{sy}^*) + o(n^{-1})$$

证毕。

定理 4.1 证明： 注意到，

$$\begin{aligned} B(\hat{t}_{cy}^*) &= E_1 E_2 \left(\frac{N}{n} \sum_s \hat{t}_i^* - t \right) \\ &= E_1 \left[\frac{N}{n} \sum_s E_2(\hat{t}_i^*) - t \right] \\ &= \sum_{i=1}^N [E_2(\hat{t}_i^*) - t_i] \\ &= \sum_{i=1}^N \sum_{j=1}^{N_i} \left(\frac{p_{ij}}{p_{ij}^*} - 1 \right) y_{ij} \end{aligned}$$

且

$$\begin{aligned} V(\hat{t}_{cy}^*) &= V_1 E_2 \left(\frac{N}{n} \sum_s \hat{t}_i^* \right) + E_1 V_2 \left(\frac{N}{n} \sum_s \hat{t}_i^* \right) \\ &= V_1 \left[\frac{N}{n} \sum_s E_2(\hat{t}_i^*) \right] + \frac{N^2}{n^2} E_1 \left[\sum_s V_2(\hat{t}_i^*) \right] \\ &= \frac{N(N-n)}{n(N-1)} \sum_{i=1}^N (t_i^* - \bar{t}^*)^2 + \frac{N}{n} \sum_{i=1}^N V_2(\hat{t}_i^*) \end{aligned}$$

这里 $t_i^* = \sum_{j=1}^{N_i} \frac{p_{ij}}{p_{ij}^*} y_{ij}$, $\bar{t}^* = \frac{1}{N} \sum_{i=1}^N t_i^*$ 且 $V_2(\hat{t}_i^*) = \frac{1}{n_i} \sum_{j=1}^{N_i} \frac{p_{ij} y_{ij}^2}{p_{ij}^{*2}} - \frac{1}{n_i} \left(\sum_{j=1}^{N_i} \frac{p_{ij} y_{ij}}{p_{ij}^*} \right)^2$ 。因此，有

$$\text{MSE}(\hat{t}_{cy}^*) = \left[\sum_{i=1}^N \sum_{j=1}^{N_i} \left(\frac{p_{ij}}{p_{ij}^*} - 1 \right) y_{ij} \right]^2 + \frac{N(N-n)}{n(N-1)} \sum_{i=1}^N (t_i^* - \bar{t}^*)^2 + \frac{N}{n} \sum_{i=1}^N V_2(\hat{t}_i^*) \quad (7)$$

证毕。

定理 4.2 证明： 记 K_i 为第 i 个群中的修正点，则根据定义 2.1 可知 K_i 有界。进一步，可推

出

$$\left[\sum_{i=1}^N \sum_{j=1}^{N_i} \left(\frac{p_{ij}}{p_{ij}^*} - 1 \right) y_{ij} \right]^2, \left[\sum_{i=1}^N \sum_{j=1}^{N_i} \left(\frac{n_i p_{ij} - n_i p_{ij}^*}{n_i p_{ij}^*} \right) y_{ij} \right]^2, C \left[\sum_{i=1}^N K_i \right]^2 = O(N^2) \setminus * \text{MERGEFORMAT} \quad (8)$$

根据定理 2.2 和定理 2.3, 有

$$\frac{N}{n} \sum_{i=1}^N V_2(\hat{t}_i) - \frac{N}{n} \sum_{i=1}^N V_2(\hat{t}_i^*) = \frac{N}{n} \sum_{i=1}^N [V_2(\hat{t}_i) - V_2(\hat{t}_i^*)] = o \left(\frac{N}{n} \sum_{i=1}^N \frac{N_i^2}{n_i} \right) \setminus * \text{MERGEFORMAT} \quad (9)$$

注意到

$$\begin{aligned} N \left| \bar{t}^{*2} - \bar{t}^2 \right|, N \left| \bar{t}^* - \bar{t} \right| \left| \bar{t}^* + \bar{t} \right| \\ = \left| \sum_{i=1}^N (t_i^* - t_i) \right| \left| \frac{1}{N} \sum_{i=1}^N (t_i^* + t_i) \right| \\ = \left| \frac{1}{N} \sum_{i=1}^N \sum_{j=1}^{N_i} \frac{n_i p_{ij} - n_i p_{ij}^*}{n_i p_{ij}^*} y_{ij} \right| \left| \sum_{i=1}^N \sum_{j=1}^{N_i} \frac{p_{ij} + p_{ij}^*}{p_{ij}^*} y_{ij} \right| \\ \leq C \left(\frac{1}{N} \sum_{i=1}^N K_i \right) \left(\sum_{i=1}^N N_i \right) = O \left(\sum_{i=1}^N N_i \right) \end{aligned}$$

因此

$$\begin{aligned} \sum_{i=1}^N (t_i - \bar{t})^2 - \sum_{i=1}^N (t_i^* - \bar{t}^*)^2 &= \sum_{i=1}^N (t_i^2 - t_i^{*2}) + N (\bar{t}^{*2} - \bar{t}^2) \\ &= \sum_{i=1}^N \left(1 - \frac{p_{ij}^2}{p_{ij}^{*2}} \right) y_{ij}^2 + O \left(\sum_{i=1}^N N_i \right) \setminus * \text{MERGEFORMAT} \quad (10) \end{aligned}$$

结合式 (6) ~ (10), 比较 THH 和 TIHH 的均方误差得到

$$\begin{aligned} \text{MSE}(\hat{t}_{cy}) - \text{MSE}(\hat{t}_{cy}^*) &= \frac{N(N-n)}{n(N-1)} \left[\sum_{i=1}^N (t_i - \bar{t})^2 - \sum_{i=1}^N (t_i^* - \bar{t}^*)^2 \right] \\ &\quad + \frac{N}{n} \sum_{i=1}^N [V_2(\hat{t}_i) - V_2(\hat{t}_i^*)] - \left[\sum_{i=1}^N \sum_{j=1}^{N_i} \left(\frac{p_{ij}}{p_{ij}^*} - 1 \right) y_{ij} \right]^2 \\ &= \frac{N(N-n)}{n(N-1)} \sum_{i=1}^N \left(1 - \frac{p_{ij}^2}{p_{ij}^{*2}} \right) y_{ij}^2 + O \left(\sum_{i=1}^N N_i \right) \\ &\quad + o \left(\frac{N}{n} \sum_{i=1}^N \frac{N_i^2}{n_i} \right) + O(N^2) \\ &= \frac{N(N-n)}{n(N-1)} \sum_{i=1}^N \left(1 - \frac{p_{ij}^2}{p_{ij}^{*2}} \right) y_{ij}^2 + O \left(\sum_{i=1}^N N_i \right) \end{aligned}$$

这里最后一个等式成立是由于 $n/N \rightarrow \lambda_0$ 且 $n_i/N_i \rightarrow \lambda_i$ 。再根据 $p_{ij}^* - p_{ij} \dots 0$, 有

$$\text{MSE}(\hat{t}_{cy}^*) \leq \text{MSE}(\hat{t}_{cy}) + O \left(\sum_{i=1}^N N_i \right)$$

证毕。