Should I Stop or Should I Go: Updated Theorems and Proofs

1. Theorems

Theorem 3.2 (CLASH weights converge to optimal weights)**.** *The CLASH weights satisfy the error bound*

$$|\hat{w}_i^n - w_i^*| \leq \exp\Big\{ - \tfrac{(\tau(x_i)-\delta)^2}{2\hat{\sigma}^2_{n,-i}(x_i)} \Big\} + \tfrac{|\hat{\tau}_{n,-i}(x_i)-\tau(x_i)|}{\hat{\sigma}_{n,-i}(x_i)} \exp\Big\{ - \tfrac{(\tau(x_i)-\delta)^2}{2\hat{\sigma}^2_{n,-i}(x_i)} + \tfrac{|\tau(x_i)-\delta||\hat{\tau}_{n,-i}(x_i)-\tau(x_i)|}{\hat{\sigma}^2_{n,-i}(x_i)} \Big\}.$$

Moreover, if $\delta < \inf_{x:\tau(x)>0} \tau(x)$ *and, given* x_i, $\hat{\tau}_{n,-i}(x_i) \xrightarrow{p} \tau(x_i)$ *and* $\hat{\sigma}_{n,-i}(x_i) \xrightarrow{p} 0$, *then* $\hat{w}_i^n$ *is a consistent estimator of the optimal weight:* $\hat{w}_i^n - w_i^* \xrightarrow{p} 0$.

Theorem 3.3 (CLASH limits unnecessary stopping)**.** *Consider a stopping test with weighted z-statistic and weights estimated using CLASH. If* $\max_{i\leq n} \hat{\sigma}^2_{n,-i}(x_i) = o_p(1/\log(n))$, $\max_{i\leq n} |\tau(x_i) - \hat{\tau}_{n,-i}(x_i)| = o_p(1)$, *and* y_i *are uniformly bounded, then the stopping probability of the test converges to zero if no participant group is harmed.*

2. Proofs

We now present proofs for all theoretical results described in the main text. Note that we repeatedly use the following property. For any events A and B,

$$\begin{aligned}
\mathbb{P}(A) &= \mathbb{P}(A, B) + \mathbb{P}(A, B^c) \\
&= \mathbb{P}(A|B)P(B) + \mathbb{P}(A|B^c)P(B^c) \\
&\leq P(B) + \mathbb{P}(A|B^c) \qquad (5)
\end{aligned}$$

where B and B^c partition the sample space.

2.1. Proof of Thm. 3.2

Our entire proof will be carried out conditional on the value x_i. Recall that we define our weights as

$$\hat{w}_i^n = 1 - \Phi\Big(\frac{\delta - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big)$$

Further recall that the functions $\hat{\tau}_{n,-i}$ and $\hat{\sigma}_{n,-i}$ are, by construction, independent of x_i.

Error Bound We first establish a bound on the difference between our estimated weights $\hat{w}_i^n$ and the optimal weights w_i^*. Consider two cases.

Case 1: $\tau(x_i) \leq 0$. In this case, $w_i^* = 0$ by definition, and so we just need to prove a bound on the magnitude of $\hat{w}_i^n$. Using Taylor's theorem with Lagrange remainder, we know that $\exists h_n \in [0, 1]$ such that

$$\begin{aligned}
\hat{w}_i^n &= 1 - \Phi\Big(\frac{\delta - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) \\
&= 1 - \Phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) - \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)} \phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)} + h_n \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) \\
&\leq 1 - \Phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) + \frac{|\tau(x_i) - \hat{\tau}_{n,-i}(x_i)|}{\hat{\sigma}_{n,-i}(x_i)} \phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)} + h_n \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big)
\end{aligned}$$

where ϕ is the standard Gaussian probability density function. Since $\delta - \tau(x_i) > 0$, we can use the Chernoff inequality to bound the first term,

$$1 - \Phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) \leq \exp\Big(-\frac{(\delta - \tau(x_i))^2}{2\hat{\sigma}^2_{n,-i}(x_i)}\Big).$$

We now focus on the second term.

$$\begin{aligned}
\phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)} + h_n \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) &= \frac{1}{\sqrt{2\pi}} \exp\Bigg\{-\frac{1}{2}\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)} + h_n \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big)^2\Bigg\} \\
&= \frac{1}{\sqrt{2\pi}} \exp\Bigg\{-\frac{1}{2}\Bigg[\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big)^2 + h_n^2\Big(\frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big)^2 - \\
&\qquad 2h_n \frac{(\delta - \tau(x_i))(\hat{\tau}_{n,-i}(x_i) - \tau(x_i))}{\hat{\sigma}^2_{n,-i}(x_i)}\Bigg]\Bigg\} \\
&\leq \exp\Bigg\{-\frac{1}{2}\Bigg[\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big)^2 - 2h_n \frac{(\delta - \tau(x_i))|\hat{\tau}_{n,-i}(x_i) - \tau(x_i)|}{\hat{\sigma}^2_{n,-i}(x_i)}\Bigg]\Bigg\} \\
&\leq \exp\Bigg\{-\frac{1}{2}\Bigg[\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big)^2 - 2\frac{(\delta - \tau(x_i))|\hat{\tau}_{n,-i}(x_i) - \tau(x_i)|}{\hat{\sigma}^2_{n,-i}(x_i)}\Bigg]\Bigg\},
\end{aligned}$$

since $h_n \in [0, 1]$. Thus, we have that

$$\hat{w}^n_i \leq \exp\Bigg\{-\frac{(\delta - \tau(x_i))^2}{2\hat{\sigma}^2_{n,-i}(x_i)}\Bigg\} + \frac{|\tau(x_i) - \hat{\tau}_{n,-i}(x_i)|}{\hat{\sigma}_{n,-i}(x_i)} \exp\Bigg\{-\frac{(\delta - \tau(x_i))^2}{2\hat{\sigma}^2_{n,-i}(x_i)} + \frac{(\delta - \tau(x_i))|\hat{\tau}_{n,-i}(x_i) - \tau(x_i)|}{\hat{\sigma}^2_{n,-i}(x_i)}\Bigg\}.$$

Case 2: $\tau(x_i) > 0$. In this case, $w^*_i = 1$. Thus,

$$\begin{aligned}
|\hat{w}^n_i - w^*_i| &= 1 - \hat{w}^n_i \\
&= \Phi\Big(\frac{\delta - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_i(x_i)}\Big) \\
&= \Phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) + \frac{|\tau(x_i) - \hat{\tau}_{n,-i}(x_i)|}{\hat{\sigma}_{n,-i}(x_i)} \phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)} + h_n \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) \\
&= 1 - \Phi\Big(\frac{\tau(x_i) - \delta}{\hat{\sigma}_{n,-i}(x_i)}\Big) + \frac{|\tau(x_i) - \hat{\tau}_{n,-i}(x_i)|}{\hat{\sigma}_{n,-i}(x_i)} \phi\Big(\frac{\delta - \tau(x_i)}{\hat{\sigma}_{n,-i}(x_i)} + h_n \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}\Big) \\
&\leq \exp\Bigg\{-\frac{(\delta - \tau(x_i))^2}{2\hat{\sigma}^2_{n,-i}(x_i)}\Bigg\} + \frac{|\tau(x_i) - \hat{\tau}_{n,-i}(x_i)|}{\hat{\sigma}_{n,-i}(x_i)} \exp\Bigg\{-\frac{(\delta - \tau(x_i))^2}{2\hat{\sigma}^2_{n,-i}(x_i)} + \frac{(\tau(x_i) - \delta)|\hat{\tau}_{n,-i}(x_i) - \tau(x_i)|}{\hat{\sigma}^2_{n,-i}(x_i)})\Bigg\}.
\end{aligned}$$

using the same Taylor expansion and Chernoff bound from above.

In summary, we have established that

$$|\hat{w}^n_i - w^*_i| \leq \exp\Bigg\{-\frac{(\delta - \tau(x_i))^2}{2\hat{\sigma}^2_{n,-i}(x_i)}\Bigg\} + \frac{|\tau(x_i) - \hat{\tau}_{n,-i}(x_i)|}{\hat{\sigma}_{n,-i}(x_i)} \exp\Bigg\{-\frac{(\delta - \tau(x_i))^2}{2\hat{\sigma}^2_{n,-i}(x_i)} + \frac{|\tau(x_i) - \delta||\hat{\tau}_{n,-i}(x_i) - \tau(x_i)|}{\hat{\sigma}^2_{n,-i}(x_i)})\Bigg\}.$$

Consistency of $\hat{w}^n_i$ We now establish the consistency of $\hat{w}^n_i$ using the derived bound. We assume that $\delta < \inf_{x:\tau(x)>0} \tau(x)$ and, given x_i, $\hat{\tau}_{n,-i}(x_i) \xrightarrow{p} \tau(x_i)$ and $\hat{\sigma}_{n,-i}(x_i) \xrightarrow{p} 0$.

Define $a_i = |\tau(x_i) - \delta|/\sqrt{2}$ and $Z_{i,n} = \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}$. From the error bound, we have that

$$|\hat{w}^n_i - w^*_i| \leq \exp(-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2) + |Z_{i,n}| \exp[-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2 + \sqrt{2}a_i|Z_{i,n}|/\hat{\sigma}_{n,-i}(x_i)].$$

Define $a = (\inf_{x:\tau(x)>0} \tau(x) - \delta)/\sqrt{2}$ and fix any $\epsilon > 0$. Then, applying equation (5),

$$\begin{aligned}
\mathbb{P}(|\hat{w}_i^n - w_i^*| > \epsilon) \leq & \mathbb{P}(\exp(-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2) + |Z_{i,n}| \exp[-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2 + \sqrt{2}a_i|Z_{i,n}|/\hat{\sigma}_{n,-i}(x_i)] > \epsilon) \\
= & \mathbb{P}(\exp(-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2) + |Z_{i,n}| \exp[-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2 + \sqrt{2}a_i|Z_{i,n}|/\hat{\sigma}_{n,-i}(x_i)] > \epsilon, \\
& \quad |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| > a/(2\sqrt{2})) + \\
& \mathbb{P}(\exp(-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2) + |Z_{i,n}| \exp[-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2 + \sqrt{2}a_i|Z_{i,n}|/\hat{\sigma}_{n,-i}(x_i)] > \epsilon, \\
& \quad |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| \leq a/(2\sqrt{2})) \\
\leq & \mathbb{P}(|Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| > a/(2\sqrt{2})) + \\
& \mathbb{P}(\exp(-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2) + |Z_{i,n}| \exp[-a_i^2/\hat{\sigma}_{n,-i}(x_i)^2 + \sqrt{2}a_i|Z_{i,n}|/\hat{\sigma}_{n,-i}(x_i)] > \epsilon \;\Big| \\
& \quad |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| \leq a/(2\sqrt{2})) \\
\leq & \mathbb{P}(|Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| > a/(2\sqrt{2})) + \mathbb{P}\left(\left(1 + \frac{a}{2\sqrt{2}\hat{\sigma}_{n,-i}(x_i)}\right) \exp\left(\frac{-a^2}{2\hat{\sigma}_{n,-i}(x_i)^2}\right) > \epsilon\right)
\end{aligned}$$

where the last inequality follows by substituting $|Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| \leq a/(2\sqrt{2})$ into bound and algebraically simplifying. Now, the first term on the right converges to 0 since $Z_{i,n}\hat{\sigma}_{n,-i}(x_i) = \tau(x_i) - \hat{\tau}_{n,-i}(x_i) \xrightarrow{p} 0$. We examine the second term. Define $\xi_{i,n} = a/(\sqrt{2}\hat{\sigma}_{n,-i}(x_i))$. Since a convex function is no smaller than its tangent line, we have $(1 + \xi_{i,n}/2) \leq \exp(\xi_{i,n}/2)$. Then,

$$\begin{aligned}
\mathbb{P}\left(\left(1 + \frac{a}{2\sqrt{2}\hat{\sigma}_{n,-i}(x_i)}\right) \exp\left(\frac{-a^2}{2\hat{\sigma}_{n,-i}(x_i)^2}\right) > \epsilon\right) &\leq \mathbb{P}\big((1 + \xi_{i,n}/2)\exp(-\xi_{i,n}^2) > \epsilon\big) \\
&\leq \mathbb{P}(\exp(-\xi_{i,n}^2 + \xi_{i,n}/2) > \epsilon)
\end{aligned}$$

which converges to 0 as $\hat{\sigma}_{n,-i}(x_i) \xrightarrow{p} 0$ (and thus $\xi_{i,n}$ diverges in probability to ∞). Thus, we have shown that

$$\mathbb{P}(|\hat{w}_i^n - w_i^*| > \epsilon) \to 0,$$

which establishes the desired consistency.

2.2. Proof of Thm. 3.3

Suppose that no participant group is harmed so that $w_i^* = 0$ for all i. Define $a = (\inf_{x:\tau(x)>0} \tau(x) - \delta)/\sqrt{2}$ and $Z_{i,n} = \frac{\tau(x_i) - \hat{\tau}_{n,-i}(x_i)}{\hat{\sigma}_{n,-i}(x_i)}$. From the proof of Thm. 3.2, we know that conditional on $|Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| \leq a/(2\sqrt{2})$,

$$\hat{w}_i^n \leq \left(1 + \frac{a}{2\sqrt{2}\hat{\sigma}_{n,-i}(x_i)}\right) \exp\left(\frac{-a^2}{2\hat{\sigma}_{n,-i}(x_i)^2}\right)$$

Fix any $\epsilon > 0$, let $\xi_{i,n} = a/(\sqrt{2}\hat{\sigma}_{n,-i}(x_i))$, and define $f(x) = (1 + x/2)\exp(-x^2)$. As in the proof of Thm. 3.2, we can apply equation (5) to write,

$$\begin{aligned}
\mathbb{P}(\textstyle\sum_i \hat{w}_i^n > \epsilon) \leq & \mathbb{P}(\max_{i\leq n} |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| > a/(2\sqrt{2})) + \mathbb{P}(\textstyle\sum_i \hat{w}_i^n > \epsilon \;\big|\; \max_{i\leq n} Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| \leq a/(2\sqrt{2})) \\
\leq & \mathbb{P}(\max_{i\leq n} |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| > a/(2\sqrt{2})) + \\
& \mathbb{P}(\textstyle\sum_i (1 + a/(2\sqrt{2}\hat{\sigma}_{n,-i}(x_i)))\exp(-a^2/2\hat{\sigma}_{n,-i}(x_i)^2) > \epsilon) \\
= & \mathbb{P}(\max_{i\leq n} |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| > a/(2\sqrt{2})) + \mathbb{P}(\textstyle\sum_i f(\xi_{i,n}) > \epsilon).
\end{aligned}$$

Since $\max_{i\leq n} |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| = o_p(1)$ by assumption, we have $\mathbb{P}(\max_{i\leq n} |Z_{i,n}\hat{\sigma}_{n,-i}(x_i)| > a/(2\sqrt{2})) \to 0$. Meanwhile, since a convex function is no smaller than its tangent line, we have $(1 + x/2) \leq \exp(x/2)$ and hence

$$f(x) \leq \exp(-x^2 + x/2) \leq \exp(-x^2 + x^2/2 + 1/8) = \exp(-x^2/2 + 1/8)$$

where we used the arithmetic-geometric mean inequality in the final inequality. Therefore,

$$\begin{aligned}\mathbb{P}(\textstyle\sum_i f(\xi_{i,n}) > \epsilon) &\leq \mathbb{P}(\textstyle\sum_i \exp(-\xi_{i,n}^2/2 + 1/8) > \epsilon) \leq \mathbb{P}(n \exp(-(\min_{i \leq n} \xi_{i,n}^2)/2 + 1/8) > \epsilon) \\ &= \mathbb{P}(\exp(-a^2/(4 \max_{i \leq n} \hat{\sigma}_{n,-i}^2(x_i)) + 1/8 + \log n) > \epsilon)\end{aligned}$$

Since $\max_{i \leq n} \hat{\sigma}_{n,-i}^2(x_i) = o_p(1/\log(n))$ by assumption, we further have $\mathbb{P}(\sum_i f(\xi_{i,n}) > \epsilon) \to 0$. Since $\epsilon > 0$ was arbitrary, we have shown that $\sum_{i=1}^n \hat{w}_i^n \xrightarrow{p} 0$.

Now, recall the form of the CLASH weighted z-statistic

$$\lambda_n^w = \frac{\sqrt{\sum_{1=1}^n \hat{w}_i^n}}{\sqrt{2\sigma^2}} \left(\frac{\sum_{i=1}^n \hat{w}_i^n y_i d_i}{\sum_{1=1}^n \hat{w}_i^n d_i} - \frac{\sum_{i=1}^n \hat{w}_i^n y_i (1 - d_i)}{\sum_{1=1}^n \hat{w}_i^n (1 - d_i)} \right)$$

Define c such that $|y_i| \leq c$. We know c must exist, since the outcomes are bounded by assumption. Then, we have that

$$\begin{aligned}|\lambda_n^w| &= \left| \frac{\sqrt{\sum_{1=1}^n \hat{w}_i^n}}{\sqrt{2\sigma^2}} \left(\frac{\sum_{i=1}^n \hat{w}_i^n y_i d_i}{\sum_{1=1}^n \hat{w}_i^n d_i} - \frac{\sum_{i=1}^n \hat{w}_i^n y_i (1 - d_i)}{\sum_{1=1}^n \hat{w}_i^n (1 - d_i)} \right) \right| \\ &\leq \frac{\sqrt{\sum_{1=1}^n \hat{w}_i^n}}{\sqrt{2\sigma^2}} \left(\frac{\sum_{i=1}^n \hat{w}_i^n c d_i}{\sum_{1=1}^n \hat{w}_i^n d_i} - \frac{\sum_{i=1}^n \hat{w}_i^n (-c) (1 - d_i)}{\sum_{1=1}^n \hat{w}_i^n (1 - d_i)} \right) \\ &= \frac{\sqrt{\sum_{1=1}^n \hat{w}_i^n}}{\sqrt{2\sigma^2}} 2c \\ &\xrightarrow{p} 0\end{aligned}$$

Thus, we see that the weighted test statistic λ_n^w converges in probability to 0. Now, the test can only reject if λ_n^w exceeds a fixed and positive bound b_α. By the definition of convergence in probability, this probability must shrink to zero.