

8 Proofs

Proposition 1. *Let $\hat{\mu}$ be defined as in Eq.(3). If Eq.(4) is satisfied for some $\zeta \in (0, 1)$ and $c > 0$, then*

$$\Pr \left[|\hat{\mu} - \mathbb{E}[Y]| > r + \frac{Z_{(m-k)} - Z_{(1+k)}}{2} \right] \leq \zeta. \quad (5)$$

Proof of Proposition 1. Whenever $\mathbb{E}[Z] \leq Z_{(m-k)} + r$ and $\mathbb{E}[Z] \geq Z_{(1+k)} - r$, we have

$$\begin{aligned} |\hat{\mu} - \mathbb{E}[Y]| &= \left| \mathbb{E}[Z] - \frac{Z_{(m-k)} + Z_{(1+k)}}{2} \right| \\ &= \max \left(\mathbb{E}[Z] - \frac{Z_{(m-k)} + Z_{(1+k)}}{2}, \right. \\ &\quad \left. \frac{Z_{(m-k)} + Z_{(1+k)}}{2} - \mathbb{E}[Z] \right) \\ &\leq \max \left(Z_{(m-k)} + r - \frac{Z_{(m-k)} + Z_{(1+k)}}{2}, \right. \\ &\quad \left. \frac{Z_{(m-k)} + Z_{(1+k)}}{2} - Z_{(1+k)} + r \right) \\ &= \frac{Z_{(m-k)} - Z_{(1+k)}}{2} + r \end{aligned}$$

In other words, we cannot have

$$|\hat{\mu} - \mathbb{E}[Y]| > \frac{Z_{(m-k)} - Z_{(1+k)}}{2} + r$$

unless either $\mathbb{E}[Z] > Z_{(m-k)} + r$ or $\mathbb{E}[Z] < Z_{(1+k)} - r$ is true, which implies that

$$\begin{aligned} \Pr \left[|\hat{\mu} - \mathbb{E}[Y]| > r + \frac{Z_{(m-k)} - Z_{(1+k)}}{2} \right] \\ \leq \Pr[\mathbb{E}[Z] > Z_{(m-k)} + r \text{ or } \mathbb{E}[Z] < Z_{(1+k)} - r] \\ \leq \Pr[\mathbb{E}[Z] > Z_{(m-k)} + r] + \Pr[\mathbb{E}[Z] < Z_{(1+k)} - r] \\ \leq \zeta \end{aligned}$$

□

Theorem 1. *Let $Z_{(1)}, \dots, Z_{(m)}$ denote the order statistics of m independent samples of a random variable Z . If Z is s -resilient, $\forall \zeta \in (0, 1), T \in \mathbb{N}$ and $0 \leq k < m/2$, then letting r be the output of Algorithm 1, we have*

$$\Pr [Z_{(m-k)} \leq \mathbb{E}[Z] - r] \leq \zeta \quad (6)$$

$$\Pr [Z_{(1+k)} \geq \mathbb{E}[Z] + r] \leq \zeta \quad (7)$$

If Z is s -resilient from above/below, then only Eq.(6)/Eq.(7) holds.

Proof of Theorem 1. Before proving Theorem 1, we first need a Lemma.

Lemma 2. *If Z is s -resilient from above, then $\forall \delta \in (0, 1)$,*

$$\Pr \left[Z \leq \mathbb{E}[Z] - s(\delta) \frac{1 - \delta}{\delta} \right] \leq \delta.$$

For some $r \in \mathbb{R}$, let B_r be the event $Z \leq \mathbb{E}[Z] - r$.

$$\begin{aligned} \Pr [Z_{(m-k)} \leq \mathbb{E}[Z] - r] \\ &= \Pr \left[\sum_{j=0}^m \mathbb{I}(Z_j \notin B_r) \leq k \right] \\ &= \sum_{i=0}^k \binom{m}{i} \Pr[B_r]^{m-i} (1 - \Pr[B_r])^i \quad (8) \\ &\leq \left(\sum_{i=0}^k \binom{m}{i} (1 - \Pr[B_r])^i \right) \Pr[B_r]^{m-k} \\ &\leq \left(\sum_{i=0}^k (m(1 - \Pr[B_r]))^i \right) \\ &\leq (m(1 - \Pr[B_r]) + 1)^k \Pr[B_r]^{m-k} \end{aligned}$$

Now we will show that the algorithm chooses v_i , $i = 0, \dots, T$ such that

$$(m(1 - v_i) + 1)^k v_i^{m-k} \leq \zeta \quad (9)$$

To show this we first show that $v_{i+1} \geq v_i$, $\forall i = 0, \dots, T-1$. This is obviously true for $i = 0$ because $0 \leq v_0 \leq 1$ so

$$\begin{aligned} v_0 &= \left(\frac{\zeta}{(m+1)^k} \right)^{\frac{1}{m-k}} \\ &\leq \left(\frac{\zeta}{(m(1 - v_0) + 1)^k} \right)^{\frac{1}{m-k}} = v_1 \end{aligned}$$

and we can proceed to use induction and conclude

$$\begin{aligned} v_i &= \left(\frac{\zeta}{(m(1 - v_{i-1}) + 1)^k} \right)^{\frac{1}{m-k}} \\ &\leq \left(\frac{\zeta}{(m(1 - v_i) + 1)^k} \right)^{\frac{1}{m-k}} = v_{i+1} \end{aligned}$$

Now we use induction to show that Eq.(9) is true. First at iteration 0 this is true because

$$(m(1 - v_0) + 1)^k v_0^{m-k} \leq (m+1)^k v_0^{m-k}$$

which is less than ζ as long as

$$v_0 \leq \left(\frac{\zeta}{(m+1)^k} \right)^{\frac{1}{m-k}}$$

Suppose Eq.(9) is true at iteration i , then at iteration $i+1$ it is still true. Denote the values as v_i and v_{i+1} . Because we choose v_{i+1} such that

$$(m(1 - v_i) + 1)^k v_{i+1}^{m-k} = \zeta$$

Observe that $v_{i+1} \geq v_i$ it must be true that

$$(m(1 - v_{i+1}) + 1)^k v_{i+1}^{m-k} \leq \zeta$$

After we have established Eq.(9) we can apply Lemma 2 to achieve $\Pr[B_r] \leq v$ it suffices to have

$$r \geq s(v)(v^{-1} - 1)$$

What remains is to prove Lemma 2

Proof of Lemma 2. Let B_r be the event $Z \leq \mathbb{E}[Z] - r$ for any $r \geq 0$. Suppose it is true that $\Pr[B_r] = \delta_r$ for some $\delta_r \in (0, 1)$, we have

$$\begin{aligned} \mathbb{E}[Z] &= \mathbb{E}[Z|B_r] \Pr[B_r] + \mathbb{E}[Z|\bar{B}_r](1 - \Pr[B_r]) \\ &\leq (\mathbb{E}[Z] - r)\delta_r + (\mathbb{E}[Z] + s(\delta_r))(1 - \delta_r) \end{aligned}$$

which implies that

$$r \leq s(\delta_r) \frac{1 - \delta_r}{\delta_r}$$

which implies

$$\Pr \left[Z \leq \mathbb{E}[Z] - s(\delta) \frac{1 - \delta}{\delta} \right] \leq \delta$$

□

□

Corollary 1. *If Z is $b_1(1 - \epsilon)^a + b_2$ resilient for any constants $a \in [-1, 0]$ and $b_1, b_2 \in \mathbb{R}^+$, then there exists $\lambda > 0$ such that for sufficiently large m*

$$\begin{aligned} \Pr \left[\mathbb{E}[Z] \leq Z_{(1+k)} - \lambda \frac{\log \frac{1}{\zeta} + k \log m}{m^{1+a}} \right] &\leq \zeta \\ \Pr \left[\mathbb{E}[Z] \geq Z_{(m-k)} + \lambda \frac{\log \frac{1}{\zeta} + k \log m}{m^{1+a}} \right] &\leq \zeta. \end{aligned}$$

Proof of Corollary 1. Denote $\epsilon = \left(\frac{\zeta}{(m+1)^k} \right)^{\frac{1}{m-k}}$. We know that

$$\lim_{m \rightarrow \infty} \log \epsilon = \frac{1}{m-k} (\log \zeta - k \log(m+1)) = 0$$

which implies $\lim_{m \rightarrow \infty} \epsilon = 1$, so $\forall a < 0$ there must exist a M such that $\forall m \geq M$, $(1 - \epsilon)^a + b \leq 2(1 - \epsilon)^a$, and $\epsilon > 1/2$

$$r \leq 2(1 - \epsilon)^a (\epsilon^{-1} - 1) = \frac{2(1 - \epsilon)^{1+a}}{\epsilon} \leq 4(1 - \epsilon)^{1+a}$$

Observe that $\epsilon < 1$ so $1 - \epsilon < -\log \epsilon$ so we have (for sufficiently large m)

$$\begin{aligned} r &\leq 4(-\log \epsilon)^{1+a} \\ &= 4 \left(-\frac{1}{m-k} \log \zeta + \frac{k}{m-k} \log(m+1) \right)^{1+a} \\ &\leq \frac{5}{m^{1+a}} \left(\log \frac{1}{\zeta} + k \log m \right)^{1+a} \\ &\leq \frac{5}{m^{1+a}} \left(\log \frac{1}{\zeta} + k \log m \right) \end{aligned}$$

Now we only need the special case of $a = 0$, where

$$r \leq (1 + b)(\epsilon^{-1} - 1) \leq 2(1 + b)(1 - \epsilon)$$

and the proof will follow as before. □

Lemma 1. *The following random variables are resilient:*

1. **Bounded:** *If $Z \subseteq [a, b]$, then Z is $(b - \mathbb{E}[Z])$ -resilient from above and $(\mathbb{E}[Z] - a)$ -resilient from below. It is $(b - a)$ -resilient.*
2. **Bounded Moments:** *If $\mathbb{E}[|Z - \mathbb{E}[Z]|^l] \leq \sigma^l$ for some $l > 1$, then Z is s -resilient for $s(\epsilon) = \frac{\sigma}{(1-\epsilon)^{1/l}}$.*
3. **Sub-Gaussian:** *If $Z - \mathbb{E}[Z]$ is σ^2 sub-Gaussian, then Z is s -resilient for $s(\epsilon) = \sqrt{2\sigma \log \frac{1}{1-\epsilon}} + \sqrt{2\pi}\sigma$.*

Proof of Lemma 1. Part 1 is trivial to prove. Part 2 is proved in Steinhardt (2018), Example 2.7. Part 3 is proven here.

Let F denote the CDF of Z . For convenience, let $\bar{\epsilon} = 1 - \epsilon$, $\tau = F^{-1}(\bar{\epsilon})$, and without loss of generality assume $\mathbb{E}[Z] = 0$. We first consider lower bounds on $\mathbb{E}[Z | Z \in B]$ where B is any subset of \mathcal{Z} such that $\Pr[Z \in B] \geq \bar{\epsilon}$. It is easy to see that for any such B we have

$$\mathbb{E}[Z | Z \leq \tau] \leq \mathbb{E}[Z | Z \in B]$$

so we only have to provide a lower bound for $\mathbb{E}[Z | Z \leq \tau]$. Without loss of generality we can also assume $\tau \leq 0$ because suppose $\tau > 0$ then consider an alternative random variable \tilde{Z} defined by $\tilde{Z} = \max(Z, 0)$. Then \tilde{Z} is σ^2 sub-Gaussian, and

$$\mathbb{E}[Z | Z \leq \tau] \geq \mathbb{E}[\tilde{Z} | \tilde{Z} \leq \tau]$$

Then we can provide a lower bound for $\mathbb{E}[\tilde{Z} | \tilde{Z} \leq \tau]$

instead. Given the above setup we have □

$$\begin{aligned}
 & \bar{\epsilon} \mathbb{E}[Z|Z \leq \tau] \\
 &= \int_{x=-\infty}^{\tau} x F'(x) dx = \int_{x=-\infty}^{\tau} F'(x) \int_{y=x}^0 (-1) dy dx \\
 &= - \int_{x=-\infty}^{\tau} \int_{y=x}^0 F'(x) dy dx \\
 &= - \int_{x=-\infty}^{\tau} \int_{y=-\infty}^0 \mathbb{I}(y > x) F'(x) dy dx \\
 &= - \int_{y=-\infty}^0 \int_{x=-\infty}^{\tau} \mathbb{I}(y > x) F'(x) dx dy \\
 &= - \int_{y=\tau}^0 \int_{x=-\infty}^{\tau} \mathbb{I}(y > x) F'(x) dx dy \\
 &\quad - \int_{y=-\infty}^{\tau} \int_{x=-\infty}^{\tau} \mathbb{I}(y > x) F'(x) dx dy \\
 &= - \int_{y=\tau}^0 \bar{\epsilon} dy - \int_{y=-\infty}^{\tau} \int_{x=-\infty}^y F'(x) dx dy \\
 &= \bar{\epsilon} \tau - \int_{y=-\infty}^{\tau} F(y) dy \\
 &= \bar{\epsilon} \tau - \int_{x=-\infty}^{\tau} F(x) dx
 \end{aligned}$$

Let $\tilde{F}(x) = e^{-\frac{x^2}{2\sigma^2}}$. Since Z is σ^2 sub-Gaussian, by Chernoff bound we know that $\forall x < 0, F(x) \leq \tilde{F}(x)$, which also implies that whenever $F^{-1}(\bar{\epsilon}) < 0, \tilde{F}^{-1}(\bar{\epsilon}) \leq F^{-1}(\bar{\epsilon})$. Then

$$\begin{aligned}
 & \bar{\epsilon} \mathbb{E}[Z|Z \leq F^{-1}(\bar{\epsilon})] \\
 &= \bar{\epsilon} F^{-1}(\bar{\epsilon}) - \int_{x=-\infty}^{F^{-1}(\bar{\epsilon})} F(x) dx \\
 &= \bar{\epsilon} F^{-1}(\bar{\epsilon}) - \int_{x=-\infty}^{\tilde{F}^{-1}(\bar{\epsilon})} F(x) dx - \int_{x=\tilde{F}^{-1}(\bar{\epsilon})}^{F^{-1}(\bar{\epsilon})} F(x) dx \\
 &\geq \bar{\epsilon} F^{-1}(\bar{\epsilon}) - \int_{x=-\infty}^{\tilde{F}^{-1}(\bar{\epsilon})} \tilde{F}(x) dx - \int_{x=\tilde{F}^{-1}(\bar{\epsilon})}^{F^{-1}(\bar{\epsilon})} \bar{\epsilon} dx \\
 &= \bar{\epsilon} \tilde{F}^{-1}(\bar{\epsilon}) - \int_{x=-\infty}^{\tilde{F}^{-1}(\bar{\epsilon})} \tilde{F}(x) dx
 \end{aligned}$$

Finally, denote $\phi_{\sigma}(x)$ as the PDF of $\mathcal{N}(0, \sigma^2)$ and Φ_{σ} be its CDF, we have

$$\begin{aligned}
 \int_{x=-\infty}^{\tilde{F}^{-1}(\bar{\epsilon})} \tilde{F}(x) dx &= \sqrt{2\pi}\sigma \int_{x=-\infty}^{\tilde{F}^{-1}(\bar{\epsilon})} \phi_{\sigma}(x) dx \\
 &= \sqrt{2\pi}\sigma \Phi_{\sigma}(\tilde{F}^{-1}(\bar{\epsilon})) \leq \sqrt{2\pi}\sigma \bar{\epsilon}
 \end{aligned}$$

Combining these results we get

$$\begin{aligned}
 & \mathbb{E}[Z|Z \leq F^{-1}(\bar{\epsilon})] \\
 &\geq \tilde{F}^{-1}(\bar{\epsilon}) - \sqrt{2\pi}\sigma = -\sqrt{2\sigma \log \frac{1}{\bar{\epsilon}}} - \sqrt{2\pi}\sigma
 \end{aligned}$$

Corollary 2. Let $Z_{(1)}, \dots, Z_{(m)}$ denote the order statistics of m independent samples of a random variable Z . If Z is bounded in $[a, b]$, $\forall \zeta \in (0, 1), T \in \mathbb{N}$ and $0 \leq k < m/2$, then letting v_T be computed as in Algorithm 1, we have

$$\begin{aligned}
 \Pr[\mathbb{E}[Z] \leq a + v_T(Z_{(1+k)} - a)] &\leq \zeta \\
 \Pr[\mathbb{E}[Z] \geq b - v_T(b - Z_{(m-k)})] &\leq \zeta.
 \end{aligned}$$

Proof of Corollary 2. By Theorem 1 we have

$$\begin{aligned}
 \zeta &\geq \Pr(Z_{(1+k)} \geq \mathbb{E}[Z] + (\mathbb{E}[Z] - a)(v_T^{-1} - 1)) \\
 &= \Pr(Z_{(1+k)} \geq v_T^{-1} \mathbb{E}[Z] - v_T^{-1} a + a) \\
 &= \Pr(v_T Z_{(1+k)} \geq v_T a - a + \mathbb{E}[Z]) \\
 &= \Pr(\mathbb{E}[Z] \leq a + v_T(Z_{(1+k)} - a))
 \end{aligned}$$

Similarly we can conclude

$$\zeta \geq \Pr(\mathbb{E}[Z] \geq b - v_T(b - Z_{(m-k)}))$$

□

Theorem 2. Let $Z_{(1)}, \dots, Z_{(m)}$ be independent samples of Z ordered such that $\|Z_{(1)}\| \leq \dots \leq \|Z_{(m)}\|$. If Z is s -resilient, then for any r output by Algorithm 1 and for any $\zeta \in (0, 1)$, we have

$$\Pr[\|Z_{(m-k)}\| \leq \|\mathbb{E}[Z]\| - r] \leq \zeta.$$

Proof of Theorem 2. Let

$$v^* = \arg \sup_{v, \|v\|_*=1} \langle v, \mathbb{E}[Z] \rangle$$

then $\|\mathbb{E}[Z]\| = \langle v^*, \mathbb{E}[Z] \rangle$. Let $\tilde{Z}_{(1)}, \dots, \tilde{Z}_{(m)}$ be ranked such that

$$\langle v^*, \tilde{Z}_{(1)} \rangle \leq \dots \leq \langle v^*, \tilde{Z}_{(m)} \rangle.$$

Denote the event $B \subset \mathcal{Z}$ as $\{Z, \langle v^*, Z \rangle \leq \langle v^*, \mathbb{E}[Z] \rangle - r\}$ as before we have

$$\Pr[\langle v^*, \tilde{Z}_{(m-k)} \rangle \leq \langle v^*, \mathbb{E}[Z] \rangle - r] \leq (m+1)^k \Pr[B]^{m-k}$$

and we set the RHS $\leq \zeta$. It suffices to have

$$\Pr[B] \leq \left(\frac{\zeta}{(m+1)^k} \right)^{\frac{1}{m-k}}$$

Similar to Lemma 2, denote $\delta = \Pr[B]$

$$\begin{aligned}
 \langle v^*, \mathbb{E}[Z] \rangle &= \mathbb{E}[\langle v^*, Z \rangle] \\
 &= \mathbb{E}[\langle v^*, Z \rangle | B] \Pr[B] + \mathbb{E}[\langle v^*, Z \rangle | \bar{B}] (1 - \Pr[B]) \\
 &\leq (\langle v^*, \mathbb{E}[Z] \rangle - r) \delta + (\langle v^*, \mathbb{E}[Z] \rangle + s(\delta)) (1 - \delta)
 \end{aligned}$$

which implies that $\Pr[B] \leq \delta$ when $r \geq s(\delta)^{\frac{1-\delta}{\delta}} = s(\delta)(\delta^{-1} - 1)$. When this is true we have

$$\Pr[\langle v^*, \tilde{Z}_{(m-k)} \rangle \leq \|\mathbb{E}[Z]\| - r] \leq \zeta$$

If we also rank $Z_{(1)}, \dots, Z_{(m)}$ by

$$\|Z_{(1)}\| \leq \dots \leq \|Z_{(m)}\|$$

we have $\forall i \geq m - k$

$$\langle v^*, \tilde{Z}_{(m-k)} \rangle \leq \langle v^*, \tilde{Z}_{(i)} \rangle \leq \|\tilde{Z}_{(i)}\|$$

so there are at least k samples $Z_{(i)}$ with norm at least $\langle v^*, \tilde{Z}_{(m-k)} \rangle$, and we can conclude that $\langle v^*, \tilde{Z}_{(m-k)} \rangle \leq \|Z_{(m-k)}\|$ which implies

$$\Pr[\|Z_{(m-k)}\| \leq \|\mathbb{E}[Z]\| - r] \leq \zeta$$

□