

SDS 384 11: Theoretical Statistics

Lecture 7a: Efron Stein inequality

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Efron Stein inequality

- Consider n independent random variables in some metric space \mathcal{X} .
- Consider a function $g : \mathcal{X}^n \rightarrow \mathbb{R}$
- Let $Z := g(X_1, \dots, X_n)$
- We are interested in computing $\text{var}(g(X_1, \dots, X_n))$
- Define $E_i(Z) = E[Z | X_{1:i-1}, X_{i+1:n}]$

An upper bound

Theorem

$$\text{var}(Z) \leq \sum_{i=1}^n E [Z - E_i[Z]]^2$$

- Note that the RHS can be thought of sum of expectation of conditional variances
- Since $\text{var}(X) \leq E[(X - a)^2]$, we also have:

$$\text{var}(Z) \leq \sum_{i=1}^n E [Z - Z_i]^2,$$

where $Z_i = g(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n)$

An upper bound

Theorem

$$\text{var}(Z) \leq \sum_{i=1}^n E[Z - E_i[Z]]^2$$

Proof.

- For two arbitrary bounded random variables X, Y , we have:
 $E[XY] = E[E[XY|Y]] = E[YE[X|Y]]$
- Let $V := Z - E[Z]$
- Let $V_i := E[Z|X_{1:i}] - E[Z|X_{1:i-1}]$
- Clearly $V = \sum_i V_i$



$$\text{var}(Z) = E \left[\sum_i V_i \right]^2 \quad (1)$$

$$= \sum_i E[V_i^2] + 2 \sum_{i < j} E[V_i V_j] = \sum_i E[V_i^2] \quad (2)$$

- Why is the last step true? For $i > j$

$$\begin{aligned} E[V_i V_j] &= E[E[V_i V_j | X_1, \dots, X_j]] \\ &= E[V_j E[V_i | X_1, \dots, X_j]] = 0 \end{aligned}$$

- Note that for three independent random variables X, Y, Z

$$E[g(X, Y, Z)|X] = E[E[g(X, Y, Z)|X, Z]|X, Y]$$

$$\begin{aligned} LHS &= \int_{y,z} g(x, y, z) f(y, z|x) dy dz = \int_z \left(\int_y g(x, y, z) f(y|x, z) dy \right) f(z|x) dz \\ &= \int_z E[g(X, Y, Z)|X, Z] f(z|x) dz \\ &\stackrel{\text{independence}}{=} \int_z E[g(X, Y, Z)|X, Z] f(z|x, y) dz \\ &= E[E[g(X, Y, Z)|X, Z]|X, Y] \end{aligned}$$

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$$\begin{aligned}V_i^2 &= (E[Z|X_{1:i}] - E[Z|X_{1:i-1}])^2 \\&= (E[Z|X_{1:i}] - E[Z|X_{1:i-1}])^2 \\&= (E[E[Z|X_{1:n}]|X_{1:i}] - E[E[Z|X_{1:i-1}, X_{i+1:n}]|X_{1:i}])^2 \\&= (E[E[Z|X_{1:n}] - E[Z|X_{1:i-1}, X_{i+1:n}]|X_{1:i}])^2 \\&= (E[Z - E_i Z|X_{1:i}])^2 \\&\leq E[(Z - E_i Z)^2|X_{1:i}] \\E[V_i^2] &\leq E[(Z - E_i Z)^2]\end{aligned}$$

The Efron Stein inequality

Theorem

Let X'_1, \dots, X'_n denote an independent copy of X_1, \dots, X_n . Let $Z'_i = g(X_{1:i-1}, X'_i, X_{i+1:n})$. We have:

$$\text{var}(Z) \leq \frac{1}{2} \sum_i E[(Z - Z'_i)^2].$$

Proof.

- If X, Y are iid, $\text{var}(X) = \frac{E[X - Y]^2}{2}$
- Conditioned on $X_{1:i-1}, X_{i+1:n}$, Z and Z'_i are independent and so

$$E_i[Z - E_i[Z]]^2 = \frac{E_i[Z - Z'_i]^2}{2}$$

$$\text{var}(Z) \leq \sum_{i=1}^n E [Z - E_i[Z]]^2 = \sum_i \frac{E[E_i[Z - Z'_i]^2]}{2}$$

Remarks

- For $g(X_1, \dots, X_n) = \sum_i X_i$ we have an equality.
- So in some sense, sums of independent random variables are the least concentrated functions
- Consider a function with the Bounded Difference property, i.e.

$$\sup_{x_{1:n}, x'_i \in \mathcal{X}} |g(x_1, \dots, x_n) - g(x_{1:i-1} x'_i x_{i+1:n})| \leq c_i$$

- We have:

$$\text{var}(g(X)) \leq \frac{1}{2} \sum_i c_i^2$$

Example: longest common subsequence

Let X_1, \dots, X_n and Y_1, \dots, Y_n be two sequences of coin flips. Z is the length of the longest common subsequence.

$$Z = \max\{k : X_{i_1} = Y_{j_1}, \dots, X_{i_k} = Y_{j_k}\}$$

where $1 \leq i_1 < i_2 \dots$ and $1 \leq j_1 < j_2 \dots$.

- It is well known that $E[Z]/n \rightarrow \mu$ where $\mu \in [0.757, 0.837]$.
- If you change one bit of X , it can change Z by at most one, so,

$$\text{var}(Z) \leq n$$

- So Z concentrates around its mean.

Uniform deviation

For X_1, \dots, X_n iid random variables, let $\hat{P}_n(A) = \frac{1}{n} \sum_i 1(X_i \in A)$ and $P_n(A) = P(X_i \in A)$. We are interested in the quantity $Z := \sup_A |\hat{P}_n(A) - P_n(A)|$

- If we change one X_i , Z changes by $1/n$ at most.
- So $\text{var}(Z) \leq \frac{1}{2n}$ by the Efron Stein inequality.
- Can we do better?

Uniform deviation

For X_1, \dots, X_n iid random variables, let

$$Z = \sup_{f \in \mathcal{F}} \sum_j f(X_j).$$

For simplicity, assume $Ef[X_i] = 0$. We will show that the E/S inequality gives a much tighter upper bound than the one we just derived.

- $\text{var}(Z) \leq \frac{1}{2} \sum_i E[(Z - Z'_i)^2]$
- Say f^* achieves the supremum for Z and f_* achieves the supremum for Z'_i

$$\begin{aligned} f_*(X_i) - f_*(X'_i) &\leq Z - Z'_i \leq f^*(X_i) - f^*(X'_i) \\ (Z - Z'_i)^2 &\leq \max((f_*(X_i) - f_*(X'_i))^2, (f^*(X_i) - f^*(X'_i))^2) \\ &\leq \sup_{f \in \mathcal{F}} (f(X_i) - f(X'_i))^2 \end{aligned}$$

Uniform deviation

$$\begin{aligned}\text{var}(Z) &\leq \frac{1}{2} \sum_i E \left[\sup_{f \in \mathcal{F}} (f(X_i) - f(X'_i))^2 \right] \\ &\stackrel{(i)}{\leq} \sum_i E \left[\sup_{f \in \mathcal{F}} (f(X_i)^2 + f(X'_i)^2) \right] \\ &\leq 2 \sum_i E \sup_{f \in \mathcal{F}} f(X_i)^2\end{aligned}$$

- (i) uses $|2ab| \leq a^2 + b^2$
- If $f(X_i) \in [-1, 1]$ we get $\text{var}(Z) \leq 2n$
- But if the variance of $\sup_f f(X_i)$ is small we have a significant improvement.

Triangles again!

- Let $Z = \{A_{ij}\}$ and let \mathcal{S}_3 be all three tuples of nodes.

$$g(Z) = \sum_{i,j,k \in \mathcal{S}_3} A_{ij} A_{jk} A_{ik}$$

- Create Z'_{ij} by changing A_{ij} by an independent copy.

Triangles again!

- $g(Z) - g(Z'_{ij})$ is simply

$$g(Z) - g(Z'_{ij}) = \sum_{k \neq i, j} (A_{ij} - A'_{ij}) A_{ik} A_{jk}$$

$$\begin{aligned} E[(g(Z) - g(Z'_{ij}))^2] &= E(A_{ij} - A'_{ij})^2 E \left[\sum_{k \neq i, j} A_{ik} A_{jk} \right]^2 \\ &= 2p(1-p) \left[\sum_{k \neq i \neq j} E A_{ik} A_{jk} + \sum_{k \neq k' \neq i \neq j} E A_{ik} A_{jk} A_{ik'} A_{jk'} \right] \\ &\approx Cp(1-p) [np^2 + n^2 p^4] \end{aligned}$$

- So, upper bound on variance is roughly $n^3 p^3 (1-p) + n^4 p^5 (1-p)$, which matches the variance up-to a constant.

Minimum of empirical loss

Consider a function class \mathcal{F} of binary valued functions on some space \mathcal{X} . Given an iid sample $(X_i, Y_i) \in \mathcal{X} \times \{0, 1\}$, for each $f \in \mathcal{F}$ we define the empirical loss:

$$L_n(f) = \frac{1}{n} \sum_{i=1}^n \ell(f(X_i), Y_i) \quad \text{where } \ell(y, y') = 1(y \neq y')$$

Define the empirical loss as $\hat{L} = \inf_{f \in \mathcal{F}} L_n(f)$.

- Naive application of Efron Stein shows $\text{var}(\hat{L}) \leq 2/n$
- Is this enough?

Minimum of empirical loss

- Let $Z = n\hat{L}$
- Let $Z_i = \min_{f \in \mathcal{F}} \left(\sum_{j \neq i} \ell(f(X_j), Y_j) + \ell(f(X'_i), Y'_i) \right)$
- $\text{var}(Z) \leq \frac{1}{2} \sum_i E[Z - Z'_i]^2 = \sum_i E[(Z - Z'_i)^2 1(Z'_i > Z)]$
- Note that
$$0 \geq (Z - Z'_i) 1(Z'_i > Z) \geq (\ell(f^*(X_i), Y_i) - \ell(f^*(X'_i), Y'_i)) 1(Z'_i > Z)$$
- So $(Z - Z'_i)^2 1(Z'_i > Z) \leq (\ell(f^*(X_i), Y_i) - \ell(f^*(X'_i), Y'_i))^2 1(Z'_i > Z) \leq \ell(f^*(X'_i), Y'_i) 1(\ell(f^*(X_i), Y_i) = 0)$
- So, $E \sum_i (Z - Z'_i)^2 1(Z'_i > Z) \leq E \sum_{\ell(f^*(X_i), Y_i) = 0} E_{X'_i, Y'_i} \ell(f^*(X'_i), Y'_i) \leq nEL(f^*)$
- Often you can show that $EL(f^*) = E\hat{L} + O(n^{-1/2})$
- So $\text{var}(\hat{L}) \leq \frac{E\hat{L}}{n} + o(1)$

Self bounding functions

Definition

A non-negative function $g : \mathcal{X}^n \rightarrow \mathcal{R}$ has the self bounding property if there exist functions $g_i : \mathcal{X}^{n-1} \rightarrow \mathcal{R}$ such that for all $x_1, \dots, x_n \in \mathcal{X}$ and $i \in [n]$,

- $0 \leq g(x_1, \dots, x_n) - g_i(x_{1:i-1}, x_{i+1:n}) \leq 1$
- $\sum_i (g(x_1, \dots, x_n) - g_i(x_{1:i-1}, x_{i+1:n})) \leq g(x_1, \dots, x_n)$

- Clearly, $\sum_i (g(x_{1:n}) - g_i(x_{1:i-1}, x_{i+1:n}))^2 \leq g(x_1, \dots, x_n) =: Z$
- Now Theorem 1 gives:

$$\text{var}(Z) \leq \sum_i E[(Z - E_i[Z])^2] \leq \sum_i E[(Z - g_i(x_{1:i-1}, x_{i+1:n}))^2] \leq E[g(x_{1:n})]$$

- So $\text{var}(Z) \leq E[Z]$

Concentration of self bounding functions

Theorem

Consider $Z := g(X_1, \dots, X_n)$ where X_1, \dots, X_n are independent random variables. If g is self-bounding, then, for all $t \geq 0$,

$$P(Z \geq E[Z] + t) \leq \exp\left(-\frac{t^2}{2(EZ + t/3)}\right)$$

$$P(Z \leq E[Z] - t) \leq \exp\left(-\frac{t^2}{2EZ}\right)$$

Relative Stability

- A sequence of non-negative random variables $\{Z_n\}$ are said to be relatively stable if $Z_n/E[Z_n] \xrightarrow{P} 1$
- If Z_n also satisfies the self bounding property,

$$P\left(\left|\frac{Z_n}{E[Z_n]} - 1\right| \geq \epsilon\right) \leq \frac{\text{var}(Z_n)}{\epsilon^2 E[Z_n]^2} \leq \frac{1}{\epsilon^2 E[Z_n]}$$

- So as long as $E[Z_n] \rightarrow \infty$, Z_n satisfies the relative stability condition

Example: empirical processes

Consider a function class \mathcal{F} of functions in $[0, 1]$. $Z := \sup_{f \in \mathcal{F}} \sum_i f(X_i)$. We show that Z is self bounding.

- Let $Z_i := \sup_{f \in \mathcal{F}} \sum_{j \neq i} f(X_j)$
- Let f^* maximize Z and f_i maximize Z_i
- We have $0 \leq f_i(X_i) \leq Z - Z_i \leq f^*(X_i) \leq 1$
- So $\sum_i (Z - Z_i) \leq \sum_i f^*(X_i) = Z$
- Hence $\text{var}(Z) \leq E[Z]$, while a naive application of E-S will give us $\text{var}(Z) \leq n/2$

Rademacher averages

Consider a function class \mathcal{F} of functions in $[-1, 1]$. Let $\{\epsilon_i\}_1^n$ denote n independent Rademacher variables independent of X_1, \dots, X_n . The conditional Rademacher average is defined as

$$Z := E \left[\sup_{f \in \mathcal{F}} \sum_i \epsilon_i f(X_i) \mid X_{1:n} \right]$$

Z has the self bounding property and so $\text{var}(Z) \leq E[Z]$.

- Define $Z_i := E \left[\sup_{f \in \mathcal{F}} \sum_{j \neq i} \epsilon_j f(X_j) \mid X_{1:n} \right]$

- Let f^* maximize Z and f_i maximize Z_i . Note that:

$$Z - Z_i \leq E[\epsilon_i f^*(X_i) | X_{1:n}] \leq 1$$

- On the other hand,

$$Z - Z_i \geq E[\epsilon_i f_i(X_i) | X_{1:n}] = 0$$

- The last step is true because ?
- So $\sum_i (Z - Z_i) \leq Z$
- Hence Z has the self-bounding property and has $\text{var}(Z) \leq E[Z]$

