

Math 639: Lecture 7

Stein's method

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Conditional expectation

Definition

Let X be a random variable on a probability space $(\Omega, \mathcal{F}_0, \text{Prob})$ satisfying $E[|X|] < \infty$ and let \mathcal{F} be a σ -algebra, $\mathcal{F} \subset \mathcal{F}_0$. The *conditional expectation of X given \mathcal{F}* , $E[X|\mathcal{F}]$ is any random variable Y such that

- 1 $Y \in \mathcal{F}$, that is, is \mathcal{F} measurable
- 2 For all $A \in \mathcal{F}$, $\int_A X dP = \int_A Y dP$.

Conditional expectation

Lemma

If Y is a conditional expectation of integrable variable X then Y is integrable.

Proof.

Let $A = \{Y > 0\} \in \mathcal{F}$. Then

$$\begin{aligned}\int_A Y dP &= \int_A X dP \leq \int_A |X| dP \\ \int_{A^c} -Y dP &= \int_{A^c} -X dP \leq \int_{A^c} |X| dP.\end{aligned}$$

Thus $E[|Y|] \leq E[|X|]$. □

Conditional expectation

Lemma

Let X be an integrable random variable on probability space $(\Omega, \mathcal{F}_0, \text{Prob})$, with σ -field $\mathcal{F} \subset \mathcal{F}_0$, and let Y and Y' be two conditional expectations of X given \mathcal{F} . Then $Y = Y'$ \mathcal{F} -a.s.

Conditional expectation

Proof.

For each set $A \in \mathcal{F}$, $\int_A Y dP = \int_A Y' dP$. Given $\epsilon > 0$, let $A = \{Y - Y' \geq \epsilon\}$. One finds

$$0 = \int_A Y - Y' dP \geq \epsilon \text{Prob}(A).$$



Conditional expectation

Lemma

Let X be an integrable random variable on probability space $(\Omega, \mathcal{F}_0, \text{Prob})$, and let $\mathcal{F} \subset \mathcal{F}_0$ be a σ -algebra. Then there exists $Y = E[X|\mathcal{F}]$.

Conditional expectation

Proof.

- By splitting X into its positive and negative parts, we may assume that $X \geq 0$.
- Let $\mu = \text{Prob}$ and let ν be the measure on \mathcal{F} defined by

$$\nu(A) = \int_A X dP, \quad A \in \mathcal{F}.$$

- By the definition of the integral, $\nu \ll \mu$.
- Let $Y = \frac{d\nu}{d\mu}$ be the Radon-Nikodym derivative of ν with respect to μ , which is \mathcal{F} -measurable. We have, for $A \in \mathcal{F}$,

$$\int_A X dP = \nu(A) = \int_A Y dP.$$



Stein's method of Poisson Approximation

- Stein has given a general method of proving limit theorems via a perturbative method which avoids the use of characteristic functions and handles dependence
- The following discussion of Poisson Approximation is based on the article
'Two moments suffice for Poisson approximations: the Chen-Stein method' by R. Arratia, L. Goldstein, L. Gordon

Set-up

- Let I be an arbitrary index set, and for $\alpha \in I$, let X_α be a Bernoulli random variable with

$$p_\alpha = \text{Prob}(X_\alpha = 1) = 1 - \text{Prob}(X_\alpha = 0) > 0.$$

- Set

$$W = \sum_{\alpha \in I} X_\alpha, \quad \lambda = \mathbb{E}[W] = \sum_{\alpha \in I} p_\alpha, \quad \lambda \in (0, \infty).$$

Set-up

- For $\alpha \in I$, let $B_\alpha \subset I$, $\alpha \in B_\alpha$ be a 'neighborhood of dependence.'
- Set

$$b_1 = \sum_{\alpha \in I} \sum_{\beta \in B_\alpha} p_\alpha p_\beta$$

$$b_2 = \sum_{\alpha \in I} \sum_{\alpha \neq \beta \in B_\alpha} p_{\alpha\beta}, \quad p_{\alpha\beta} = E[X_\alpha X_\beta]$$

$$b_3 = \sum_{\alpha \in I} s_\alpha.$$

$$s_\alpha = E \left[\left| E \left[X_\alpha - p_\alpha \mid \sigma(X_\beta : \beta \in I - B_\alpha) \right] \right| \right].$$

Set-up

Recall the definition of the total variation norm.

Definition

If Z, W are two $\mathbb{Z}_{\geq 0}$ valued random variables with distributions (laws) $\mathcal{L}(Z), \mathcal{L}(W)$. The *total variation distance* between $\mathcal{L}(Z)$ and $\mathcal{L}(W)$ is

$$\begin{aligned}\|\mathcal{L}(Z) - \mathcal{L}(W)\|_{\text{TV}} &= \frac{1}{2} \sup_{\|h\|_{\infty}=1} |\mathbb{E}[h(W)] - \mathbb{E}[h(Z)]| \\ &= \sup_{A \subset \mathbb{Z}^+} |\text{Prob}(W \in A) - \text{Prob}(Z \in A)|.\end{aligned}$$

Stein's method of Poisson approximation

The following theorem is due to Chen.

Theorem

Let W be the number of occurrences of dependent events, and let b_1, b_2, b_3 be as in the set-up. Let Z be a $\text{Poisson}(\lambda)$ random variable. Then

$$\|\mathcal{L}(W) - \mathcal{L}(Z)\|_{\text{TV}} \leq b_1 + b_2 + b_3.$$

Stein's operators

Let λ be a parameter, let $Z \sim \text{Poisson}(\lambda)$ and define linear operators S, T on functions on $\mathbb{Z}_{\geq 0}$ by

$$Tf(w) = wf(w) - \lambda f(w + 1)$$
$$Sf(w + 1) = -\frac{\mathbb{E}[f(Z)\mathbf{1}_{(Z \leq w)}]}{\lambda \text{Prob}(Z = w)}, \quad Sf(0) = 0.$$

Stein's operators

Lemma

T and S are inverse, in the sense that $TSf = f$.

Stein's operators

Proof.

We have, for $x \neq 0$,

$$\begin{aligned}TSf(x) &= xSf(x) - \lambda Sf(x+1) \\ &= xSf(x) + \frac{E[h(Z)\mathbf{1}_{(Z \leq x)}]}{\text{Prob}(Z = x)} \\ &= -\frac{x E[f(Z)\mathbf{1}_{(Z \leq x-1)}]}{\lambda \text{Prob}(Z = x-1)} + \frac{E[f(Z)\mathbf{1}_{(Z \leq x)}]}{\text{Prob}(Z = x)} \\ &= f(x)\end{aligned}$$

For $x = 0$, $xSf(x) = 0$, the result is the same. □

Stein's criterion

Lemma

Let λ be a parameter, and let Z be a $\mathbb{Z}_{\geq 0}$ valued random variable. $Z \sim \text{Poisson}(\lambda)$ if and only if for all bounded f ,

$$E[Tf(Z)] = 0.$$

Stein's criterion

Proof.

- To check the necessity, write

$$\begin{aligned}E[Tf(Z)] &= e^{-\lambda} \sum_{n \geq 0} Tf(n) \frac{\lambda^n}{n!} \\&= e^{-\lambda} \sum_{n \geq 0} (nf(n) - \lambda f(n+1)) \frac{\lambda^n}{n!} \\&= e^{-\lambda} \sum_{n \geq 1} (f(n) - f(n)) \frac{\lambda^n}{(n-1)!} = 0.\end{aligned}$$



Stein's criterion

Proof.

- To prove the sufficiency, set $f(x) = \mathbf{1}_{(x=n)}$ for $n = 1, 2, \dots$ to obtain

$$\text{Prob}(Z = n - 1) = \frac{n}{\lambda} \text{Prob}(Z = n).$$

The result follows.



Bounding the Stein operator

Define $\Delta f(n) = f(n+1) - f(n)$.

Lemma

Suppose that $\forall w \geq 0$, $h(w) \in [0, 1]$ and $f = S(h(\cdot) - \mathbb{E}[h(Z)])$. Then

$$\|\Delta f\|_\infty \leq \frac{1 - e^{-\lambda}}{\lambda} \text{ and } \|f\|_\infty \leq \min\left(1, \frac{1.4}{\lambda^{\frac{1}{2}}}\right).$$

Furthermore, if $h(w) = \mathbf{1}(w = 0) - e^{-\lambda}$ then $\|f\|_\infty = \frac{1 - e^{-\lambda}}{\lambda}$.

Bounding the Stein operator

Proof.

- Observe

$$\begin{aligned} f(m+1) &= \frac{E[h(Z)] \text{Prob}(Z \leq m)}{\lambda \text{Prob}(Z = m)} - \frac{E[h(Z)\mathbf{1}(Z \leq m)]}{\lambda \text{Prob}(Z = m)} \\ &= \frac{E[h(Z)\mathbf{1}(Z > m)] \text{Prob}(Z \leq m)}{\lambda \text{Prob}(Z = m)} \\ &\quad - \frac{E[h(Z)\mathbf{1}(Z \leq m)] \text{Prob}(Z > m)}{\lambda \text{Prob}(Z = m)}. \end{aligned}$$

$$\text{Hence } |f(m+1)| \leq \frac{\text{Prob}(Z \leq m) \text{Prob}(Z > m)}{\lambda \text{Prob}(Z = m)}.$$



Bounding the Stein operator

Proof.

- For $m < \lambda$,

$$\begin{aligned} |f(m+1)| &\leq \frac{\text{Prob}(Z \leq m)}{\lambda \text{Prob}(Z = m)} = \frac{1}{\lambda} \sum_{j=0}^m \frac{m!}{\lambda^j (m-j)!} \\ &\leq \frac{1}{\lambda} \sum_{j=0}^m \left(\frac{m}{\lambda}\right)^j \leq (\lambda - m)^{-1}. \end{aligned}$$

Hence $|f(m)| \leq 1$ if $m \leq \lambda$.



Bounding the Stein operator

Proof.

- For $m \geq \lambda - 3$

$$\begin{aligned} |f(m+1)| &\leq \frac{\text{Prob}(Z > m)}{\lambda \text{Prob}(Z = m)} = \sum_{j=0}^{\infty} \frac{\lambda^j m!}{(m+1+j)!} \\ &\leq \frac{1}{m+1} \left[1 + \frac{\lambda}{m+2} \sum_{j=0}^{\infty} \left(\frac{\lambda}{m+3} \right)^j \right] \\ &= \frac{(m+2)(m+3) + \lambda}{(m+1)(m+2)(m+3-\lambda)}. \end{aligned}$$

This restricts bounding $|f(m)| < 1$ to a finite check, which we'll ignore. □

Bounding the Stein operator

Proof.

- Using $\text{Prob}(Z \leq m) \text{Prob}(Z > m) \leq \frac{1}{4}$ and Stirling's approximation

$$\begin{aligned} |f(m+1)| &\leq \frac{1}{4\lambda \text{Prob}(Z = m)} \\ &\leq \frac{\sqrt{2\pi}}{4\lambda^{\frac{1}{2}}} \left(\frac{m}{\lambda}\right)^{m+\frac{1}{2}} \exp\left(\lambda - m + \frac{1}{12m}\right) \\ &\leq \frac{\sqrt{2\pi}}{4} \lambda^{-\frac{1}{2}} \exp\left(\frac{(m-\lambda)(m-\lambda+\frac{1}{2})}{\lambda} + \frac{1}{12m}\right). \end{aligned}$$

Using this for $|\lambda - m| \leq \lambda^{\frac{1}{2}}$ and the previous inequalities otherwise obtains the bound $|f(m+1)| \leq \frac{C}{\lambda^{\frac{1}{2}}}$.



Bounding the Stein operator

Proof.

- Define f_j by taking $h(x) = \mathbf{1}(x = j)$. Hence

$$f_j(m+1) = \begin{cases} \lambda^{j-m-1} \frac{m!}{j!} \text{Prob}(Z > m) & m \geq j \\ -\lambda^{j-m-1} \frac{m!}{j!} \text{Prob}(Z \leq m) & m < j \end{cases}.$$

- One easily checks that f_j is positive and decreasing in $m \geq j+1$ and is negative and decreasing in $m \leq j$.
- The only positive value of $f_j(m+1) - f_j(m)$ is

$$\begin{aligned} f_j(j+1) - f_j(j) &= \frac{e^{-\lambda}}{\lambda} \left[\sum_{r=j+1}^{\infty} \frac{\lambda^r}{r!} + \sum_{r=1}^j \frac{\lambda^r}{r!} \frac{r}{j} \right] \\ &\leq \frac{e^{-\lambda}}{\lambda} (e^\lambda - 1) = \frac{1 - e^{-\lambda}}{\lambda}. \end{aligned}$$



Bounding the Stein operator

Proof.

- Writing the general f as $f = \sum_j h(j)f_j$ proves

$$f(m+1) - f(m) \leq f_m(m+1) - f_m(m) \leq \frac{1 - e^{-\lambda}}{\lambda}.$$

- This last calculation contains the claim that $\|f_0\| = \frac{1 - e^{-\lambda}}{\lambda}$ as this is the value at 1.



Proof of Stein's Poisson approximation

Proof of Stein's Poisson approximation theorem.

- Let h be given with $\|h\|_\infty = 1$ and let $Z \sim \text{Poisson}(\lambda)$.
- Let $\bar{h}(\cdot) = h(\cdot) - E[h(Z)]$, $f = S\bar{h}$ and $Tf = \bar{h}$, so

$$E[Tf(W)] = E[h(W) - h(Z)].$$



Proof of Stein's Poisson approximation

Proof of Stein's Poisson approximation theorem.

- Let $V_\alpha = \sum_{\beta \in I - B_\alpha} X_\beta$ and $W_\alpha = W - X_\alpha$. We have $X_\alpha f(W) = X_\alpha f(W_\alpha + 1)$ and $f(W_\alpha + 1) - f(W + 1) = X_\alpha [f(W_\alpha + 1) - f(W_\alpha + 2)]$.
- Calculate

$$\begin{aligned} \mathbb{E}[h(W) - h(Z)] &= \mathbb{E}[Wf(W) - \lambda f(W + 1)] \\ &= \sum_{\alpha \in I} \mathbb{E}[X_\alpha f(W) - p_\alpha f(W + 1)] \\ &= \sum_{\alpha \in I} \mathbb{E}[p_\alpha f(W_\alpha + 1) - p_\alpha f(W + 1)] \\ &\quad + \sum_{\alpha \in I} \mathbb{E}[X_\alpha f(W_\alpha + 1) - p_\alpha f(W_\alpha + 1)] \end{aligned}$$



Proof of Stein's Poisson approximation

Proof of Stein's Poisson approximation theorem.

- Calculate further

$$\begin{aligned} E[h(W) - h(Z)] &= \sum_{\alpha \in I} E[p_{\alpha} X_{\alpha} [f(W_{\alpha} + 1) - f(W_{\alpha} + 2)]] \\ &\quad + \sum_{\alpha \in I} E[(X_{\alpha} - p_{\alpha}) [f(W_{\alpha} + 1) - f(V_{\alpha} + 1)]] \\ &\quad + \sum_{\alpha \in I} E[(X_{\alpha} - p_{\alpha}) f(V_{\alpha} + 1)]. \end{aligned}$$

- The first term may be bounded by $\|\Delta f\|_{\infty} \sum_{\alpha \in I} p_{\alpha}^2$.



Proof of Stein's Poisson approximation

Proof of Stein's Poisson approximation theorem.

- To bound $\sum_{\alpha \in I} \mathbb{E}[(X_\alpha - p_\alpha)[f(W_\alpha + 1) - f(V_\alpha + 1)]]$, write $\mathbb{E}[(X_\alpha - p_\alpha)[f(W_\alpha + 1) - f(V_\alpha + 1)]]$ as a telescoping sum of $|B_\alpha| - 1$ terms of the form

$$\begin{aligned} & \mathbb{E}[(X_\alpha - p_\alpha)(f(U + X_\beta) - f(U))] \\ &= \mathbb{E}[(X_\alpha - p_\alpha)X_\beta(f(U + 1) - f(U))] \\ &= \mathbb{E}[X_\alpha X_\beta \Delta f(U)] - \mathbb{E}[p_\alpha X_\beta \Delta f(U)] \\ &\leq \|\Delta f\|_\infty (p_{\alpha\beta} + p_\alpha p_\beta). \end{aligned}$$

- Thus the second term is bounded by

$$\|\Delta f\|_\infty \sum_{\alpha \in I} \sum_{\alpha \neq \beta \in B_\alpha} (p_{\alpha\beta} + p_\alpha p_\beta).$$



Proof of Stein's Poisson approximation

Proof of Stein's Poisson approximation theorem.

- The third term is bounded by

$$\begin{aligned} & \left| \sum_{\alpha \in I} E[(X_\alpha - p_\alpha)f(V_\alpha + 1)] \right| \\ & \leq \|f\|_\infty \sum_{\alpha \in I} E \left[\left| E \left[X_\alpha - p_\alpha \mid \sum_{\beta \in I - B_\alpha} X_\beta \right] \right| \right] = \|f\|_\infty b'_3. \end{aligned}$$

- This completes the proof. □

A random graph problem

Example

- On the hypercube $\{0, 1\}^n$, assume each of the $n2^{n-1}$ edges is assigned a random direction by tossing a fair coin, and let W be the number of vertices at which all n edges point inward.
- Let I be the set of all 2^n vertices, and X_α the indicator that vertex α has all edges pointing inward. Thus $p_\alpha = 2^{-n}$. Set $\lambda = 1$, $Z = \text{Poisson}(1)$.
- $B_\alpha = \{\beta : |\alpha - \beta| \leq 1\}$.

A random graph problem

Example

- Calculate

$$b_1 = \sum_{\alpha \in I} \sum_{\beta \in B_\alpha} p_\alpha p_\beta = |I|(n+1)2^{-2n} = \frac{n+1}{2^n}.$$

- Calculate

$$b_2 = \sum_{\alpha \in I} \sum_{\alpha \neq \beta \in B_\alpha} \mathbb{E}[X_\alpha X_\beta] = 0,$$

since the events $\{X_\alpha = 1\}$ and $\{X_\beta = 1\}$ are mutually exclusive.

- $b_3 = 0$ since X_α is independent of $\sigma(X_\beta : \beta \in I - B_\alpha)$.
- $\|\mathcal{L}(W) - \mathcal{L}(Z)\|_{\text{TV}} \leq (n+1)2^{-n}$.

The birthday problem

Example

- Suppose n balls (people) are uniformly and independently distributed into d boxes (days of the year). We seek an estimate for the probability that at least one box contains k or more balls for $k = 2, 3, 4, \dots$
- Let $I = \{\alpha \subset \{1, 2, 3, \dots, n\} : |\alpha| = k\}$, and let X_α be the event that each ball in α goes into the same box.
- Set $W = \sum_{\alpha \in I} X_\alpha$, $p_\alpha = \text{Prob}(X_\alpha = 1) = d^{1-k}$, $\lambda = \binom{n}{k} d^{1-k}$ and $Z \sim \text{Poisson}(\lambda)$.
- The goal is to approximate $W \Rightarrow Z$ as $n \rightarrow \infty$. To do so, we assume that λ is held essentially fixed, so that $d \asymp n^{\frac{k}{k-1}}$ as $n \rightarrow \infty$.

The birthday problem

Example

- $B_\alpha = \{\beta \in I : \alpha \cap \beta \neq \emptyset\}$. Hence X_α is independent of $\sigma(X_\beta : \beta \in B_\alpha)$, so $b_3 = 0$.
- One has $|B_\alpha| = \binom{n}{k} - \binom{n-k}{k}$, so

$$\begin{aligned} b_1 &= p_\alpha^2 |I| |B_\alpha| \\ &= \lambda^2 \frac{|B_\alpha|}{|I|} \\ &= \lambda^2 \left(1 - \frac{n-k}{n} \frac{n-k-1}{n-1} \cdots \frac{n-2k+1}{n-k+1} \right) \\ &< \lambda^2 \left(1 - \left(1 - \frac{k^2}{n-k+1} \right) \right) = \frac{\lambda^2 k^2}{n-k+1}. \end{aligned}$$

- For λ and k fixed, this tends to 0 with increasing n .

The birthday problem

Example

- For fixed α ,

$$\sum_{\beta \in B_\alpha \setminus \{\alpha\}} \mathbb{E}[X_\alpha X_\beta] = \sum_{j=1}^{k-1} \binom{k}{j} \binom{n-k}{k-j} d^{1+j-2k}.$$

When $\frac{d}{n}$ is large, the dominant term comes from $j = k - 1$, so that

$$b_2 \lesssim k \binom{n}{k} (n-k) d^{-k} = k \lambda \frac{n-k}{d}.$$

- Recalling $d \asymp n^{\frac{k}{k-1}}$, $b_2 \rightarrow 0$.

The longest perfect head run

Example

- Let $0 < p < 1$ and Y_1, Y_2, \dots be an i.i.d. sequence
 $p = \text{Prob}(Y_i = 1) = 1 - \text{Prob}(Y_i = 0)$.
- Let R_n be the length of the longest consecutive run of heads starting within the first n tosses.
- Let $I = \{1, 2, \dots, n\}$.
- Fix positive integer t and set $X_1 = Y_1 Y_2 \cdots Y_t$, and for $2 \leq \alpha \leq n$,

$$X_\alpha = (1 - Y_{\alpha-1}) Y_\alpha Y_{\alpha+1} \cdots Y_{\alpha+t-1}.$$

The longest perfect head run

Example

- Let $B_\alpha = \{\beta \in I : |\alpha - \beta| \leq t\}$.
- One has $b_3 = 0$ by independence, and $b_2 = 0$, since for $\beta \neq \alpha$, $\beta \in B_\alpha$, the events $\{X_\alpha = 1\}$ and $\{X_\beta = 1\}$ are exclusive.
- We have

$$b_1 < p^{2t} (1 + 2t(1 - p)) + n(2t + 1)p^{2t}(1 - p)^2$$

and

$$\lambda = \lambda(n, t) = E[W] = p^t [(n - 1)(1 - p) + 1].$$

- Since $\{R_n < t\} = \{W = 0\}$, with $Z \sim \text{Poisson}(\lambda)$

$$\left| \text{Prob}(R_n < t) - e^{-\lambda(n,t)} \right| \leq \|W - Z\|_{\text{TV}} \leq b_1 \min(1, \lambda^{-1}).$$

Keeping λ fixed as $n \rightarrow \infty$, $b_1 \rightarrow 0$.

Stein's method of normal approximation

Our discussion of Stein's method of normal approximation is taken from Stein's 1986 monograph "Approximate computation of expectations."
For the remainder of the lecture Z is a standard normal random variable.

Stein's operators

- Let \mathcal{X} be the space of all piecewise continuous $h : \mathbb{R} \rightarrow \mathbb{R}$ such that, for all $k > 0$

$$\int_{-\infty}^{\infty} |x|^k |h(x)| e^{-\frac{x^2}{2}} dx < \infty.$$

- Let \mathcal{F} be the space of all continuous and piecewise continuously differentiable $f : \mathbb{R} \rightarrow \mathbb{R}$ with $f' \in \mathcal{X}$.
- Define operators $T : \mathcal{F} \rightarrow \mathcal{X}$, $Tf(w) = f'(w) - wf(w)$ and $U : \mathcal{X} \rightarrow \mathcal{F}$,

$$Uh(w) = e^{\frac{w^2}{2}} \int_{-\infty}^w [h(x) - E[h(Z)]] e^{-\frac{x^2}{2}} dx.$$

Stein's operators

Lemma

For all $f \in \mathcal{F}$, $Tf \in \mathcal{X}$. For all $h \in \mathcal{X}$, $Uh \in \mathcal{F}$. Let Z be standard normal. For $h \in \mathcal{X}$, $T \circ Uh(w) = h(w) - E[h(Z)]$.

Stein's operators

Proof.

- For $f \in \mathcal{F}$ and $k > 0$,

$$\begin{aligned} \int_0^\infty w^{k+1} |f(w) - f(0)| e^{-\frac{w^2}{2}} dw &= \int_0^\infty w^{k+1} \left| \int_0^w f'(x) dx \right| e^{-\frac{w^2}{2}} dw \\ &\leq \int_0^\infty |f'(x)| \int_x^\infty w^{k+1} e^{-\frac{w^2}{2}} dw dx \\ &\leq \int_0^\infty |f'(x)| C(1 + |x|^k) e^{-\frac{x^2}{2}} dx < \infty. \end{aligned}$$

Similarly $\int_{-\infty}^0 |w|^{k+1} |f(w) - f(0)| e^{-\frac{w^2}{2}} dw < \infty$. Hence $w \mapsto wf(w) \in \mathcal{X}$, so $Tf \in \mathcal{X}$.



Stein's operators

Proof.

- Given $h \in \mathcal{X}$, $k \geq 0$,

$$\begin{aligned} & \int_0^\infty w^{k+1} |Uh(w)| e^{-\frac{w^2}{2}} dw \\ & \leq \int_0^\infty w^{k+1} \int_w^\infty |h(x) - \mathbb{E}[h(Z)]| e^{-\frac{x^2}{2}} dx dw \\ & = \int_0^\infty |h(x) - \mathbb{E}[h(Z)]| \frac{x^{k+2}}{k+2} e^{-\frac{x^2}{2}} dx < \infty. \end{aligned}$$

Similarly $\int_{-\infty}^0 |w|^{k+1} |Uh(w)| e^{-\frac{w^2}{2}} dw < \infty$, so that $w \mapsto wUh(w) \in \mathcal{X}$.



Stein's operators

Proof.

- Differentiate

$$Uh(w) = e^{\frac{w^2}{2}} \int_{-\infty}^w [h(x) - E[h(Z)]] e^{-\frac{x^2}{2}} dx$$

to obtain $(Uh)'(w) - w(Uh)(w) = h(w) - E[h(Z)]$.



Stein's method of normal approximation

Lemma

In order that the real random variable W has a standard normal distribution, it is necessary and sufficient that, for all continuous and piecewise continuously differentiable functions $f : \mathbb{R} \rightarrow \mathbb{R}$ with $E[|f'(Z)|] < \infty$, Z standard normal, we have

$$E[f'(W)] = E[Wf(W)].$$

Stein's method of normal approximation

Proof of necessity.

Let W have a standard normal distribution. Then

$$\begin{aligned} E[f'(W)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f'(w) e^{-\frac{w^2}{2}} dw \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^0 f'(w) \left(\int_{-\infty}^w (-z) e^{-\frac{z^2}{2}} dz \right) dw \\ &\quad + \frac{1}{\sqrt{2\pi}} \int_0^{\infty} f'(w) \left(\int_w^{\infty} z e^{-\frac{z^2}{2}} dz \right) dw \end{aligned}$$



Stein's method of normal approximation

Proof of necessity.

$$\begin{aligned} &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^0 \left(\int_z^0 f'(w) dw \right) (-z) e^{-\frac{z^2}{2}} dz \\ &\quad + \frac{1}{\sqrt{2\pi}} \int_0^{\infty} \left(\int_0^z f'(w) dw \right) z e^{-\frac{z^2}{2}} dz \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} [f(z) - f(0)] z e^{-\frac{z^2}{2}} dz = E[Wf(W)]. \end{aligned}$$



Stein's method of normal approximation

Proof of sufficiency.

- Given $w_0 \in \mathbb{R}$, let $f_{w_0} = U\mathbf{1}(w \leq w_0)$.
- Hence

$$\begin{aligned} E[f'_{w_0}(W) - Wf_{w_0}(W)] &= E[\mathbf{1}(W \leq w_0) - E[\mathbf{1}(Z \leq w_0)]] \\ &= \text{Prob}(W \leq w_0) - \text{Prob}(Z \leq w_0). \end{aligned}$$

Hence, if this is zero for all w_0 then W has a standard normal distribution.



Explicit estimates

The special functions $f_{w_0} = U\mathbf{1}(w \leq w_0)$ are given by

$$f_{w_0}(w) = \begin{cases} \sqrt{2\pi} e^{\frac{w^2}{2}} \Phi(w) [1 - \Phi(w_0)] & w \leq w_0 \\ \sqrt{2\pi} e^{\frac{w^2}{2}} \Phi(w_0) [1 - \Phi(w)] & w \geq w_0 \end{cases}$$

where $\Phi(w) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^w e^{-\frac{x^2}{2}} dx$.

Explicit estimates

Lemma

The functions f_{w_0} satisfies

$$0 < f_{w_0}(w) \leq \frac{\sqrt{2\pi}}{4}, \quad |wf_{w_0}(w)| < 1, \quad |f'_{w_0}(w)| < 1$$

for all real w_0, w .

We omit this explicit calculation.

Bounds for the Stein operator

Lemma

For bounded absolutely continuous $h : \mathbb{R} \rightarrow \mathbb{R}$,

$$\|Uh\|_{\infty} \leq \sqrt{\frac{\pi}{2}} \|h - \mathbb{E}[h(Z)]\|_{\infty}$$

$$\|Uh'\|_{\infty} \leq 2 \|h - \mathbb{E}[h(Z)]\|_{\infty}$$

$$\|Uh''\|_{\infty} \leq 2 \|h'\|_{\infty}.$$

Bounds for the Stein operator

Proof.

For $w \leq 0$,

$$|Uh(w)| \leq \left[\sup_{x \leq 0} |h(x) - E[h(Z)]| \right] e^{\frac{w^2}{2}} \int_{-\infty}^w e^{-\frac{x^2}{2}} dx,$$

and, for $w \geq 0$,

$$|Uh(w)| \leq \left[\sup_{x \geq 0} |h(x) - E[h(Z)]| \right] e^{\frac{w^2}{2}} \int_w^{\infty} e^{-\frac{x^2}{2}} dx.$$

The first claim follows since the maximum of $e^{\frac{w^2}{2}} \int_{-\infty}^w e^{-\frac{x^2}{2}} dx$ in $w \leq 0$ is attained at 0. □

Bounds for the Stein operator

Proof.

For $w \geq 0$ use

$$(Uh)'(w) = h(w) - E[h(Z)] - we^{\frac{w^2}{2}} \int_w^{\infty} [h(x) - E[h(Z)]] e^{-\frac{x^2}{2}} dx.$$

Hence

$$\begin{aligned} \sup_{w \geq 0} |(Uh)'(w)| &\leq [\sup |h - E[h(Z)]|] \left[1 + \sup_{w \geq 0} we^{\frac{w^2}{2}} \int_w^{\infty} e^{-\frac{x^2}{2}} dx \right] \\ &\leq 2 \sup |h - E[h(Z)]|. \end{aligned}$$

The bound for $w \leq 0$ is similar.



Bounds for the Stein operator

Proof.

The bound for $\|(Uh)''\|_\infty$ in terms of $\|h'\|_\infty$ is a more involved computation, which we omit. □

Exchangeable pairs

Definition

A pair (X, X') of random variables on a probability space $(\Omega, \mathcal{B}, \text{Prob})$ is called an *exchangeable pair* if, for all B, B' ,

$$\text{Prob}(X \in B, X' \in B') = \text{Prob}(X \in B', X' \in B).$$

Stein's method for normal approximation

The following lemma is key.

Lemma

Let $0 < \lambda < 1$ and let (W, W') be an exchangeable pair of real random variables, such that

$$E[W'|W] = (1 - \lambda)W.$$

Let $h : \mathbb{R} \rightarrow \mathbb{R}$ be a bounded continuous function with bounded piecewise continuous derivative h' .

$$E[h(W)] = E[h(Z)] + E \left[(Uh)'(W) \left[1 - \frac{1}{2\lambda} E[(W' - W)^2 | W] \right] \right] + \frac{1}{2\lambda} \int E \left[(W - W') \left(z - \frac{W + W'}{2} \right) [\mathbf{1}(z \leq W') - \mathbf{1}(z \leq W)] \right] d(Uh)'(z)$$

Stein's method for normal approximation

Proof.

From the identity

$$\begin{aligned} 0 &= E \left[Wf(W) - \frac{1}{2\lambda}(W' - W)(f(W') - f(W)) \right] \\ &= E[Wf(W) - f'(W)] + E \left[f'(W) - \frac{1}{2\lambda}(W' - W)(f(W') - f(W)) \right] \\ &= E[h(Z)] - E[h(W)] + E[f'(W)] - \frac{1}{2\lambda} E[(W' - W)(f(W') - f(W))] \end{aligned}$$

obtain

$$E[h(W)] = E[h(Z)] + E[f'(W)] - \frac{1}{2\lambda} E[(W - W')(f(W) - f(W'))].$$



Stein's method for normal approximation

Proof.

Rewrite part of the last line as

$$\begin{aligned} & \mathbb{E} \left[f'(W) - \frac{1}{2\lambda} (W' - W)(f(W') - f(W)) \right] \\ &= \mathbb{E} \left[f'(W) \left[1 - \frac{1}{2\lambda} \mathbb{E} [(W' - W)^2 | W] \right] \right] \\ &\quad - \frac{1}{2\lambda} \mathbb{E} [(W' - W) [f(W') - f(W) - (W' - W)f'(W)]] . \end{aligned}$$



Stein's method for normal approximation

Proof.

Write

$$\begin{aligned} f(W') - f(W) - (W' - W)f'(W) &= \int_W^{W'} (W' - y)f''(y)dy \\ &= \int (W' - y)[\mathbf{1}(y \leq W') - \mathbf{1}(y \leq W)]f''(y)dy. \end{aligned}$$

Take expectation and use the exchangeability of W, W' to obtain the claim. □

Stein's method for normal approximation

Theorem

Let h be a bounded continuous function with bounded piecewise continuous derivative h' . Let W, W' as in the previous lemma. Then

$$\begin{aligned} |E[h(W)] - E[h(Z)]| &\leq \frac{1}{4\lambda} \|h'\|_\infty E[|W' - W|^3] \\ &+ 2\|h - E[h(Z)]\|_\infty \sqrt{E\left[\left(1 - \frac{1}{2\lambda} E[(W' - W)^2|W]\right)^2\right]}. \end{aligned}$$

and for all real w_0 ,

$$\begin{aligned} |\text{Prob}(W \leq w_0) - \Phi(w_0)| &\leq 2\sqrt{E\left[\left(1 - \frac{1}{2\lambda} E[(W' - W)^2|W]\right)^2\right]} \\ &+ (2\pi)^{-\frac{1}{4}} \sqrt{\frac{1}{\lambda} E[|W' - W|^3]}. \end{aligned}$$

Stein's method for normal approximation

Proof.

$$\begin{aligned} \mathbb{E}[h(W)] - \mathbb{E}[h(Z)] &= \mathbb{E} \left[(Uh)'(W) \left[1 - \frac{1}{2\lambda} \mathbb{E}[(W' - W)^2 | W] \right] \right] + \\ &\frac{1}{2\lambda} \int \mathbb{E} \left[(W - W') \left(z - \frac{W + W'}{2} \right) [\mathbf{1}(z \leq W') - \mathbf{1}(z \leq W)] \right] \\ &\quad \times (Uh)''(z) dz \end{aligned}$$

so

$$\begin{aligned} |\mathbb{E}[h(W)] - \mathbb{E}[h(Z)]| &\leq \|(Uh)'\|_{\infty} \mathbb{E} \left[\left| 1 - \frac{1}{2\lambda} \mathbb{E}[(W - W')^2 | W] \right| \right] \\ &+ \|(Uh)''\|_{\infty} \frac{1}{2\lambda} \mathbb{E} \left[\int_{\min(W, W')}^{\max(W, W')} |W - W'| \left| z - \frac{W + W'}{2} \right| dz \right]. \end{aligned}$$

□

Stein's method for normal approximation

Proof.

Recall $\|(Uh)'\|_\infty \leq 2\|h - E[h(Z)]\|_\infty$ and $\|(Uh)''\|_\infty \leq 2\|h'\|_\infty$. Hence

$$\begin{aligned} |E[h(W)] - E[h(Z)]| &\leq \\ &2\|h - E[h(Z)]\|_\infty \sqrt{E\left[\left(1 - \frac{1}{2\lambda} E[(W - W')^2|W]\right)^2\right]} \\ &+ 2\|h'\|_\infty \frac{1}{2\lambda} E\left[\frac{|W - W'|^3}{4}\right]. \end{aligned}$$

This proves the first bound.

To prove the second, bound $\mathbf{1}(w \leq w_0)$ from above and below using piece-wise linear functions. We omit the details. □