

Hidden convexity

[1]

Let $\mathbf{X} = (X_1, \dots, X_k)$ have a multivariate normal distribution, $N(0, V)$. Put $\lambda = \text{trace} V$. Show $\mathbb{P}|\mathbf{X}|^3 \leq \lambda^{3/2} \mathbb{P}|N(0, 1)|^{3/2}$. ✕ $\text{Wlog } V = \text{diag}(\sigma_1^2, \dots, \sigma_k^2)$. Convex weights $\theta_i = \sigma_i^2/\lambda$. Expectation equals $\lambda^{3/2} \mathbb{P}|\sum_i \theta_i Z_i^2|^{3/2}$ for independent standard normal Z_i . Convex function of θ maximized at extreme point.

See Pollard (1996b, Chapter 13; retrieve *PROB.Coupling.ps* from WWW site) for an exposition of the application to the Yurinskii coupling.

[2]

Bennett's Inequality: Let Y_1, \dots, Y_n be independent random variables with (i) $\mathbb{P}Y_i = 0$ and $\mathbb{P}Y_i^2 = \sigma_i^2 < \infty$ and (ii) $Y_i \leq M$ for every i , for some finite constant M . Then, for $x \geq 0$,

$$\mathbb{P}\{Y_1 + \dots + Y_n \geq x\} \leq \exp\left(-\frac{x^2}{2V} \psi\left(\frac{Mx}{V}\right)\right) \quad \text{with } V = \sigma_1^2 + \dots + \sigma_n^2,$$

where $\psi(x) = ((1+x)\log(1+x) - x)/(x^2/2)$ for $x \geq -1$.

Bernstein's Inequality: Replace $\psi(x)$ by its lower bound, $\psi(x) \geq (1 + \frac{x}{3})^{-1}$.

See Pollard (1996b, Chapter 4; retrieve *PROB.Exponential.ps* from WWW site) or Shorack & Wellner (1986, Chapter 11) for applications of the Bennett exponential inequality.

[3]

(Pinsker's/Csiszar's/Kemperman's inequality) Probability measures P and Q with densities p and q . Show $\int p \log(p/q) \geq \frac{1}{2} (\int |p - q|)^2$. ✕ Write $p/q = 1 + \delta$. Note $Q\delta = \int q(p - q)/q = 0$.

$$\begin{aligned} \text{LHS} &= Q((1 + \delta) \log(1 + \delta) - \delta) && \text{because } Q\delta = 0 \\ &\geq Q(1/2 \delta^2 \psi(\delta)) && \text{definition of } \psi \\ &\geq \frac{1}{2} Q\left(\frac{\delta^2}{1 + \delta/3}\right) Q(1 + \delta/3) && \text{lower bound for } \psi, \text{ and } Q\delta = 0 \\ &\geq \frac{1}{2} \left(Q \frac{|\delta|}{\sqrt{1 + \delta/3}} \sqrt{1 + \delta/3}\right)^2 && \text{Cauchy-Schwarz} \\ &= \text{RHS} \end{aligned}$$

[4]

Let f be a twice differentiable convex function defined on a convex interval $J \subseteq \mathbb{R}$ that contains the origin. Suppose $f(0) = f'(0) = 0$. Use the representations

$$f(t) = t \int \{0 \leq u \leq 1\} f'(tu) du = t^2 \iint \{0 \leq v \leq u \leq 1\} f''(tv) dv du = t^2 \int_0^1 (1 - v) f''(tv) dv$$

to establish the following facts. (i) The function $f(t)/t$ is increasing. (ii) The function $\phi(x) := 2f(t)/t^2$ is nonnegative. (iii) If f is convex then so is ϕ . (iv) If f'' is increasing then so is ϕ . (v) Invoke Jensen's inequality for the uniform distribution on $\{0 \leq v \leq u \leq 1\}$ to show that $\phi(t) \geq f''(t/3)$.

[5]

Perhaps optimization estimator defined to maximize process $G_n(t) = \frac{1}{n} \sum_{i \leq n} g(x_i, t)$ over t in an index set $T \subseteq \mathbb{R}$. Empirical process $v_n g = n^{-1/2} \sum_{i \leq n} (g(x_i) - \mathbb{P}g(x_i))$.

Signal plus noise split: $G_n(t) = \mathbb{P}G_n(t) + n^{-1/2} v_n^x g(x, t)$.

Taylor: $g(x, t) - g(x, 0) - t g'(x, 0) = t \int_0^1 (g'(x, tu) - g'(x, 0)) du$.

Stochastic Taylor: $v_n^x g(x, t) = v_n^x g(x, 0) + t v_n^x g'(x, 0) + R_n(t)$, where

$$\sup_{|t| \leq \delta} \frac{|R_n(t)|}{|t|} = \sup_{|t| \leq \delta} |v_n^x \int_0^1 (g'(x, tu) - g'(x, 0)) du| \leq \sup_{|s| \leq \delta} |v_n^x (g'(x, s) - g'(x, 0))|.$$

Stochastic equicontinuity condition for empirical process indexed by $\{g'(\cdot, t) : t \in T\}$ gives $R_n(t) = o_p(|t|)$ uniformly in shrinking neighborhoods of $t = 0$.

See Pollard (1996a, Chapter 13; retrieve *ASY.RatesCid.ps* from WWW site) for applications of uniform stochastic approximations in the study of asymptotics for optimization estimators.

6

(Kim & Pollard 1990, Lemma 2.6). “Let $\{Z(t) : t \in T\}$ be a Gaussian process with continuous sample paths, indexed by a σ -compact metric space. If $\text{var}(Z(s) - Z(t)) \neq 0$ for all $s \neq t$ then, with probability one, no sample path can achieve its maximum at two distinct points of T .” Reduce proof to convexity fact: “If Γ_0 and Γ_1 are convex functions on \mathbb{R} with infimum of right-hand derivative of Γ_0 strictly greater than supremum of right-hand derivative of Γ_1 , then $\Gamma_0(z) = \Gamma_1(z)$ for at most one value of z .”

7

Unimodality of $S = X_1 + \dots + X_n$, where the X_i are independent and X_i is $\text{Bin}(1, p_i)$ distributed. Show ratios $\mathbb{P}\{S = k\}/\mathbb{P}\{S = k - 1\}$ decrease as k increases. That is, show

$$\mathbb{P}\{S = k + 1\}\mathbb{P}\{S = k - 1\} \leq \mathbb{P}\{S = k\}^2.$$

✂ Independent copy $T = X'_1 + \dots + X'_n$. Condition on the $W_i = X_1 + X'_i$. Generate X_i and X'_i from W_i : toss fair coin if $W_i = 1$. If n_j of the W_i equal j (for $j = 0, 1, 2$) then number of heads H has $\text{Bin}(n_1, 1/2)$ conditional distribution. $\mathbb{P}\{S = k, T = k \mid \mathbf{W}\}$ is zero unless $2k = n_1 + 2n_2$, in which case conditional probability equals $\mathbb{P}\{H = n_1/2 \mid \mathbf{W}\}$, which is greater than $\mathbb{P}\{H = 1 + n_1/2 \mid \mathbf{W}\}$. For more surprising consequences see Samuels (1965) and Jogdeo & Samuels (1968).

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