

# BERNSTEIN'S INEQUALITY IN THE BIVARIATE CASE

BY  
KENNETH MULLEN

**SUMMARY.** If  $X_1, X_2, \dots, X_n$ , is a set of  $n$  independent random variables, such that  $EX_i=0$ ,  $\text{Var}(X_i)=\sigma_i^2$ , and if  $t$  is a real positive number and  $\sigma^2=\sum_i \sigma_i^2$ , then Bernstein [2] has given an upper bound for  $\Pr[\sum X_i \geq t\sigma]$  when the  $X$ 's are bounded. The best English language discussion of Bernstein's work is probably by Bennett [1]. In this paper we consider the bivariate case where random vectors  $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$  are observed, where  $EX_i=EY_i=0$ ,  $\text{Var}(X_i)=\text{Var}(Y_i)=\sigma_i^2$ ,  $EX_i Y_i = \rho \sigma_i^2$ . An expression for the upper bound for  $\Pr[\sum X_i \geq t\sigma, \sum Y_i \geq t\sigma]$  is given when both  $X$  and  $Y$  are bounded.

**Derivation.**

**THEOREM.** Let  $t, a$ , and  $b$  be real positive numbers and consider  $n$  independent random variables  $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$  where  $EX_i=EY_i=0$ ,  $\text{Var}(X_i)=\text{Var}(Y_i)=\sigma_i^2$ ,  $EX_i Y_i = \rho \sigma_i^2$ ,  $\sigma^2 = \sum_{i=1}^n \sigma_i^2$  and for which  $|X_i| \leq R, |Y_i| \leq R$ , then

$$P\left[\sum_i X_i \geq t\sigma, \sum_i Y_i \geq t\sigma\right] < \exp\left\{\frac{-t^2(2 - |\rho|)}{2\left(1 + \frac{tR}{3\sigma}\right)}\right\}.$$

**Proof.** Consider  $e^{aX_i + bY_i}$ , then

$$e^{aX_i + bY_i} = \left\{1 + aX_i + \sum_{r=2}^{\infty} \frac{a^r X_i^r}{r!}\right\} \left\{1 + bY_i + \sum_{s=2}^{\infty} \frac{b^s Y_i^s}{s!}\right\}.$$

Expanding, taking expectations, and noting that  $EaX_i = EbY_i = 0$ , we get

$$Ee^{aX_i + bY_i} = 1 + ab\rho\sigma_i^2 + \frac{a^2\sigma_i^2 A_i}{2} + \frac{b^2\sigma_i^2 B_i}{2} + ab\sigma_i^2(C_i + D_i + E_i)$$

where

$$\begin{aligned} A_i &= \sum_{r=2}^{\infty} \frac{a^{r-2} EX_i^r}{r! \sigma_i^{\frac{r}{2}}} \\ B_i &= \sum_{s=2}^{\infty} \frac{b^{s-2} EY_i^2}{s! \sigma_i^{\frac{s}{2}}} \\ C_i &= \sum_{r=2}^{\infty} \frac{a^{r-1} EY_i X_i^r}{r! \sigma_i^2} \\ D_i &= \sum_{s=2}^{\infty} \frac{b^{s-1} EX_i Y_i^s}{s! \sigma_i^2} \\ E_i &= \sum_{r=2}^{\infty} \sum_{s=2}^{\infty} \frac{a^{r-1} b^{s-1} EX_i^r Y_i^s}{r! s! \sigma_i^2}. \end{aligned} \tag{1}$$

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Thus we can write

$$Ee^{aX_i+bY_i} < \exp\left\{\left(\frac{a^2\sigma_i^2}{2} + \frac{b^2\sigma_i^2}{2}\right)M_i + ab\sigma_i^2G_i\right\}$$

where  $M_i = \text{Max}(A_i, B_i)$ ,

$$G_i = \rho + C_i + D_i + E_i.$$

Now if  $S(X) = \sum_{i=1}^n X_i$ ,  $S(Y) = \sum_{i=1}^n Y_i$  then

$$Ee^{aS(X)+bS(Y)} < \exp\left\{\left(\frac{a^2\sigma^2}{2} + \frac{b^2\sigma^2}{2}\right)M + ab\sigma G\right\}$$

where  $M = \max M_i$ ,  $G = \max G_i$ .

Let  $h(X, Y)$  be a nonnegative function of  $X$  and  $Y$  with p.d.f.  $f(x, y)$ , so that  $h(X, Y) > K$  when  $X \geq C_1$ ,  $Y \geq C_2$ .

$$\begin{aligned} E[h(X, Y)] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(x, y)f(x, y) dx dy \geq \int_{x \geq C_1} \int_{y \geq C_2} h(x, y)f(x, y) dx dy \\ &\geq K \int_{x \geq C_1} \int_{y \geq C_2} f(x, y) dx dy = K \cdot P[X \geq C_1, Y \geq C_2]. \end{aligned}$$

Now if  $h(X, Y) = \exp(aX + bY)$  then

$$P[X \geq C_1, Y \geq C_2] \leq \frac{E \exp(aX + bY)}{\exp(aC_1 + bC_2)}.$$

Replace  $X$  by  $S(X)$ ,  $Y$  by  $S(Y)$ ,  $C_1 = C_2 = t\sigma$ , then

$$\begin{aligned} P[S(X) \geq t\sigma, S(Y) \geq t\sigma] &\leq \frac{E \exp(aS(X) + bS(Y))}{\exp((a+b)(t\sigma))} \\ &< \exp\left\{\left(\frac{a^2\sigma^2}{2} + \frac{b^2\sigma^2}{2}\right)M + ab\sigma^2G - (t\sigma)(a+b)\right\}. \end{aligned}$$

This right-hand side is minimized with respect to  $a$  and  $b$  for

$$\begin{aligned} a\sigma^2M + b\sigma^2G &= t\sigma \\ b\sigma^2M + a\sigma^2G &= t\sigma \end{aligned}$$

i.e. when

$$(2) \quad M = \frac{t}{\sigma(a+b)}, \quad G = \frac{t}{\sigma(a+b)}.$$

Thus we can write:

$$(3) \quad P[S(X) \geq t\sigma, S(Y) \geq t\sigma] < \exp\left\{\frac{-t\sigma(a+b)}{2}\right\}.$$

Now suppose that

$$\begin{aligned} E |X_i|^r &\leq \frac{1}{2}\sigma_i^2 r! W^{r-2} \\ E |Y_i|^s &\leq \frac{1}{2}\sigma_i^2 s! W^{r-2} \end{aligned} \quad \left. \begin{array}{l} r, s \geq 2 \\ W \text{ a constant} \end{array} \right\}$$

then since  $EX_i^r \leq E |X_i|^r$  we have

$$A_i \leq \frac{1}{1-aW}, \quad B_i \leq \frac{1}{1-bW}.$$

Now without loss of generality assume  $a > b$  ( $a = b$  can be omitted), so that we can state  $M_i \leq (1 - aW)^{-1}$ , which being independent of  $i$  implies that

$$(4) \quad M \leq \frac{1}{1 - aW}.$$

Further suppose that

$$\begin{aligned} E |Y_i| |X_i|^r &\leq |\rho| \sigma_i^2 r! W^{r-1} \\ E |X_i| |Y_i|^s &\leq |\rho| \sigma_i^2 s! W^{s-1} \\ E |X_i|^r |Y_i|^s &\leq |\rho| \sigma_i^2 r! s! W^{r-1} W^{s-1} \end{aligned}$$

where  $r, s \geq 2$ ,  $W$  is a constant, then

$$\begin{aligned} C_i &\leq \frac{|\rho| aW}{1 - aW} \\ D_i &\leq \frac{|\rho| bW}{1 - bW} \\ E_i &\leq \frac{|\rho| abW^2}{(1 - aW)(1 - bW)}. \end{aligned}$$

Noting that the right-hand sides are independent of  $i$ , we have

$$(5) \quad \begin{aligned} G &\leq |\rho| \left\{ 1 + \frac{aW}{1 - aW} + \frac{bW}{1 - bW} + \frac{abW^2}{(1 - aW)(1 - bW)} \right\} \\ &= \frac{|\rho|}{(1 - aW)(1 - bW)}. \end{aligned}$$

Let us now choose  $W$  so that

$$(6) \quad 1 - bW \leq |\rho|$$

then from (4), (5), and (6)

$$M = \frac{t}{\sigma(a + b)} \leq \frac{1}{1 - aW} \leq \frac{|\rho|}{(1 - aW)(1 - bW)}$$

Taking the left most inequality yields

$$a \geq \frac{t - \sigma b}{\sigma + tW}$$

which, when put into (3) gives

$$P[S(X) \geq t\sigma, S(Y) \geq t\sigma] < \exp\left\{ \frac{-t^2\sigma(1 + bW)}{2(\sigma + tW)} \right\}.$$

Using (6) gives

$$P[S(X) \geq t\sigma, S(Y) \geq t\sigma] < \exp\left\{ \frac{-t^2(2 - |\rho|)}{2(\sigma - tW)} \right\}$$

or

$$(7) \quad P[S(X) \geq t\sigma, S(Y) \geq t\sigma] < \exp\left\{ \frac{-t^2(2 - |\rho|)}{2\left(1 + t\frac{W}{\sigma}\right)} \right\}.$$

Of particular interest are bounded variables satisfying

$$|X_i| \leq R, \quad |Y_i| \leq R$$

for which

$$\begin{aligned} E |X_i|^r &\leq \sigma_i^2 R^{r-2}, & E |Y_i|^s &\leq \sigma_i^2 R^{s-2} \\ E |Y_i| |X_i|^r &\leq |\rho| \sigma_i^2 R^{r-1} \\ E |X_i| |Y_i|^s &\leq |\rho| \sigma_i^2 R^{s-1} \\ E |X_i|^r |Y_i|^s &\leq |\rho| \sigma_i^2 R^{s-1} R^{r-1} \end{aligned}$$

so that  $W=3R$  is the smallest value of  $W$  that can be used. Then (7) becomes

$$(8) \quad P[S(X) \geq t\sigma, S(Y) \geq t\sigma] < \exp\left\{\frac{-t^2(2 - |\rho|)}{2\left(1 + \frac{tR}{3}\right)}\right\}$$

and the proof is complete. When  $|\rho|=1$  and we have in effect only one random variable, then (8) reduces to the univariate case (see Reference [1]). When  $|\rho|=0$ , (8) is the product of two univariate cases.

#### REFERENCES

1. George Bennett, *Probability inequalities for the sum of independent random variables*, J. Amer. Statist. Assoc. 57 (1962), 33–45.
2. S. Bernstein, *Sur une modification de l'inégalité de Tchebichef* (in Russian, French Summary), Ann. Sci. Inst. Sev. Ukraine Sect. Math. I, 1924.

UNIVERSITY OF GUELPH,  
GUELPH, ONTARIO